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COMPARATIVE PERFORMANCE OF SEQUENTIAL CNN AND PRE-TRAINED LEARNING FOR 3D PRINTING DEFECT CLASSIFICATION

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Abstract*—3D Printing is currently needed in various industries, including education in terms of research development. In this study, researchers classify 3D printing defect images to recognize images that are difficult to see with the naked eye. With limited observation, an image classification method is needed to help users detect defects in the printing process with a Deep Learning model. The printing process uses PLA and ABS-based filament materials, which are mostly used in 3D Printing objects with fused deposition modeling (FDM)-based 3D Printer machines. In this study, there are several stages, including data augmentation, model development using sequential CNN, pre-trained CNN based with pre-trained models, namely VGG-16 and VGG-19, training, validation, and model evaluation. The dataset taken for training is 1557, with a ratio of 80 percent training and 20 percent validation between defective and non-defective objects. The results of this study have a good accuracy value on Sequential CNN with an accuracy of 99.68% compared to pre-trained CNN models, namely VGG-16 and VGG-19. The classification results are also compared with other additive manufacturing classification methods with different machines and materials such as metal and 3D Food Printing which are measured based on classification model optimization analysis.*

Keywords*: 3D Printing, CNN, Classification, Pre-trained.*

Intisari—*3D Printing saat ini dibutuhkan dalam berbagai industri, termasuk pendidikan dalam hal pengembangan penelitian. Dalam penelitian ini, peneliti mengklasifikasikan gambar cacat 3D printing untuk mengenali gambar yang sulit dilihat dengan mata telanjang. Dengan keterbatasan pengamatan, diperlukan metode klasifikasi gambar untuk membantu pengguna mendeteksi cacat pada proses pencetakan dengan model Deep Learning. Proses cetak menggunakan bahan filamen berbasis PLA dan ABS, yang sebagian besar digunakan pada objek 3D Printing dengan mesin 3D Printer berbasis fused deposition modeling (FDM). Dalam penelitian ini, ada beberapa tahapan, diantaranya augmentasi data, pengembangan model menggunakan CNN sequential, CNN berbasis pre-trained dengan model yang telah dilatih sebelumnya, yaitu VGG-16 dan VGG-19, proses training, validasi, serta evaluasi model. Dataset yang diambil untuk pelatihan berjumlah 1557, dengan rasio 80 persen training dan 20 persen validation antara objek defect dan no defect. Hasil penelitian ini memiliki nilai akurasi yang baik pada CNN Sequential dengan akurasi 99,68% dibandingkan dengan model CNN berbasis pre-trained, yaitu VGG-16 dan VGG-19. Hasil klasifikasi juga dibandingkan dengan metode klasifikasi additive manufacturing lainnya dengan mesin dan material yang berbeda sseperti metal dan 3D Food Printing yang diukur berbasis analisis optimasi model klasifikasi.*

Kata Kunci*: Pencetakan 3D, CNN, Klasifikasi, Pra-latih..*

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INTRODUCTION

3D printing technology is currently the latest technology that is widely used by humans for various needs [1]. 3D printing is included in the largest additive manufacturing technology used to make prototype models, action figures, and others [2]. Currently, 3D printing is needed in the health sector to make medical devices, as designing devices using conventional methods is difficult [3]. In terms of time efficiency, if print failures are not addressed by print monitoring technology, there will be wasted time due to the need to restart the printing process from the beginning.

Furthermore, in terms of observation, if only manual monitoring is used, defective objects in 3D prints cannot produce precise object models. Visual monitoring, with limited capabilities, will be a problem [4]. The primary difficulty with 3D printing is the possibility of printing process failure, which could lead to faulty objects [5]. The defective result is a loss for the user because it results in the loss of material and inefficiency [6]. Therefore, it is necessary to have a technology that is able to monitor and classify images to separate which objects are defect and no defect [7]. It takes a computer vision method that is able to classify 3D Printing defective objects, one of which is deep learning [8].

Compared to machine learning models, the Convolutional Neural Network (CNN) performs more effectively and efficiently during the computational process, making it the best deep learning model [9]. In the pre-trained CNN model, the CNN architecture had previously achieved victory in the ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) for its performance in image classification tasks [10]. 2014 saw the debut of VGG16. Five convolutional and pooling layers make up this model, which is completed with a fully connected layer. There are 138 million parameters in this model. DenseNet, meanwhile, debuted in 2016. Compared to VGG16, this model has a significantly smaller number of parameters (8 million).

This model utilizes each initial layer, which is continuously connected to the next layer until the final layer, ensuring that all learned features are continuously utilized until the end. Several pre-trained models have been tested for object detection and classification, including VGG-16 and VGG-19 [11]. VGG16 is a CNN model that utilizes convolutional layers with a small convolutional filter specification (3x3). More convolutional layers can be added to the neural network's depth to increase accuracy, thanks to this convolutional filter size. Three fully connected layers and sixteen convolutional layers make up the 19 layers of the VGG16 model [12].

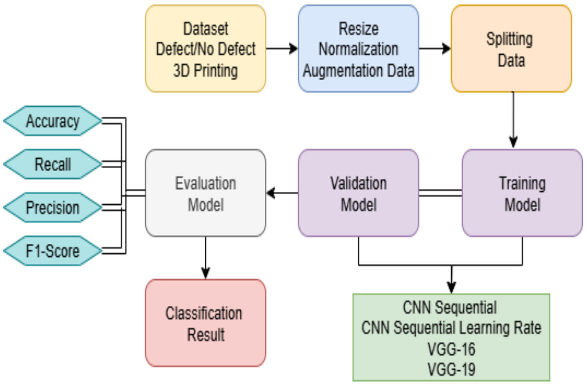
Some studies that have been conducted on the classification process of additive manufacturing objects using CNN models and other deep learning include research by Westphal et al. with selective laser sintering additive manufacturing that have an accuracy value of 95.8% [13]. Then Zhou et al.'s research with Ceramic 3D Printing objects has an accuracy of 97.2% [14]. From the literature study above, this research was conducted to classify defective objects in 3D printing made from PLA and ABS with optimal performance results. This research compares the classification results between Sequential CNN models with hyperparameter learning rate, as well as CNN based on pre-trained learning, namely VGG-16 and VGG-19.

MATERIALS AND METHODS

The dataset at the initial stage, as illustrated in Figure 1, was categorized into two classes: defect and no defect. Afterward, preprocessing steps such as resizing and normalization were applied to reduce image resolution and enhance pattern recognition accuracy. To improve the model's generalization ability and reduce the risk of overfitting the training data, a data augmentation process was performed. This technique aims to artificially expand the variety of training data without manually increasing the number of images.

In this study, three main transformations were applied: horizontal flipping, rotation, and zooming. First, the RandomFlip("horizontal") layer is used to flip the image horizontally with a random probability, allowing the model to learn to recognize objects even if their orientation differs from the original data. Second, the RandomRotation(0.1) layer provides a random rotation of 10% of the maximum angle, which helps the model become more robust to different shooting angles. Third, the RandomZoom(0.1) layer enlarges or shrinks the image by up to 10% of its original size, allowing the model to adapt to variations in the distance between the camera and the object. In the training and validation process, the model used a CNN and pre-trained learning.

There are four models used in the training process, namely CNN Sequential, CNN Sequential with adjusted learning rate, VGG-16 and VGG-19. Furthermore, model evaluation is carried out to measure model performance with accuracy, recall, precision, and F1-score parameters [15].

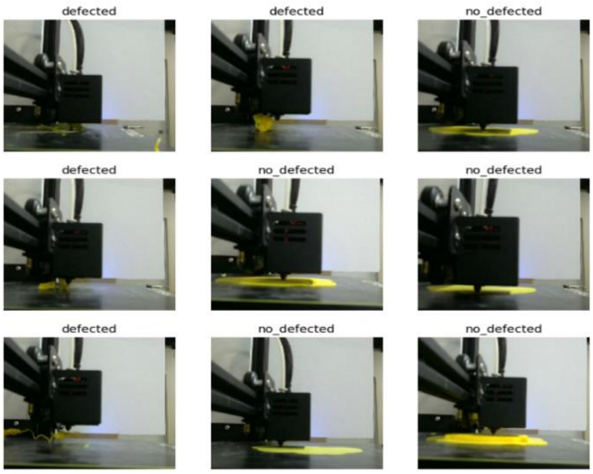


Source : (Research Results, 2025)

Figure 1. Research Stages

Dataset

The dataset was obtained from the Kaggle database, which is available at https://www.kaggle.com/datasets/justin900429/3d-printer-defected-dataset, as shown in Figure 2.



Source : (Justin Ruan, 2022)

Figure 2. Dataset Defect & No_Defect 3D Printing

The dataset on 3D Printing Image is 1557, divided into 759 defect data and 798 no_defect data, with the data using the CNN model will be trained as much as 1246, and validated 311. As seen in Table 1, in the defect class, 605 for training data, 154 for validation. In the no defect class, 641 were used for training data, and 157 were used for validation.

Table 1. Distribution of Dataset

No	Categorry	Training	Validation	Total
1	Defect	605	154	759
2	No Defect	641	157	758

(Research Results, 2025)

Architecture Model

CNN with a sequential architecture was employed to build the image classification model. The first design consisted of multiple convolutional layers with cascaded filters (16, 32, and 64) using a 5 × 5 kernel, followed by a MaxPooling2D layer to reduce feature dimensionality. The extracted features were subsequently flattened and forwarded to a dense layer consisting of 128 neurons with a ReLU activation function, before being mapped to an output layer whose neuron count corresponded to the number of dataset classes. The model was compiled using the Adam optimizer, accuracy as the evaluation metric, and a loss function suited to classification. Initial training over 15 epochs was assessed through accuracy and loss curves on both training and validation sets. Since the results showed signs of overfitting, data augmentation was introduced using Keras' Sequential API with random zoom, rotation, and horizontal flip transformations [16]. The goal of augmentation is to enrich the variety of image data so that the model is more capable of generalization [17].

A second CNN architecture was then constructed by adding an augmentation layer to the input stage, followed by normalization, three 3 × 3 convolutional layers with filters (16, 32, 64), a pooling layer, and a Dropout of 0.2 to reduce the risk of overfitting. Next, the resulting features were flattened, processed with a dense layer of 128 units, and projected to the output layer according to the number of classes. The compilation process continued using the Adam optimizer with the same configuration. The second model was trained for 30 epochs, and evaluation results showed improved stability and validation accuracy compared to the first model.

Next, a comparison was conducted using pre-trained CNNs VGG-16 and VGG-19 [18][19]. The VGG-16 and VGG-19 architectures are well-established convolutional models that have demonstrated strong performance in diverse image classification tasks. Developed at the University of Oxford, these models emphasize the use of small 3 × 3 convolutional filters, stacked deeply to enable hierarchical extraction of visual features. The fundamental difference between the two models lies in the number of convolutional layers: 16 in VGG-16 and 19 in VGG-19, which conceptually provides a higher feature representation capacity in VGG-19.

In this study, both models functioned as feature extractors, initialized with ImageNet weights, while the final fully connected layer was adjusted to align with the number of classes in the extrusion-based 3D printing defect dataset. To ensure training stability and minimize overfitting on the limited data, all convolutional weights were frozen. A Dense layer consisting of 256 neurons

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with ReLU activation and a 0.5 Dropout rate was incorporated to enhance generalization. The training was conducted for 20 epochs using the Adam optimizer with a learning rate of 0.0001. Sparse Categorical Cross-Entropy was used as the loss function. It is appropriate for multi-class classification problems with integer-encoded labels and enables effective training without requiring one-hot encoding. The overall training configuration is summarized in Table 2.

Table 2. Hyperparameter Model

Learning Rate	Optimizer	Loss Function	Epochs	Batch Size
0,0001	Adam	SparsecategoricalCross	15, 20, 30	16, 32, 64

Source: (Research Results, 2025)

Evaluation Model

To evaluate model performance in this study, a Confusion Matrix was used to visualize the model's performance results. The distribution of accurate and inaccurate classifications within each class is shown by the Confusion Matrix. Next, a classification report is presented, displaying precision, recall, and f1-score metrics, allowing for insight into the model's performance across both defect and no-defect categories. Thus, this study successfully developed a systematic pipeline, from dataset loading, data preprocessing, initial CNN model formation, data augmentation strategy, to performance evaluation using accuracy metrics, the Confusion Matrix, and the classification report. These results demonstrate that the CNN approach with data augmentation can improve the model's ability to detect defects in extrusion-based 3D printed products and can serve as the basis for developing an automated detection system for the 3D printing-based food manufacturing industry. The equations for accuracy, recall, precision, and F1-score are shown in equations (1), (2), (3), and (4) [20].

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

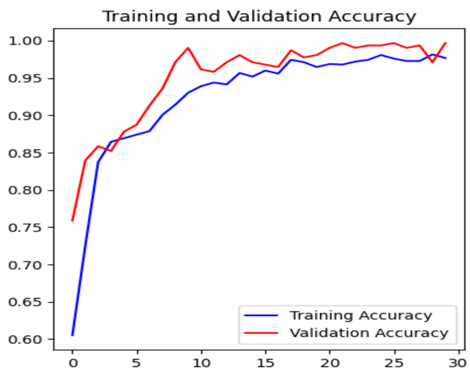
$$Precision = \frac{(TP)}{(TP+FP)} \quad (2)$$

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

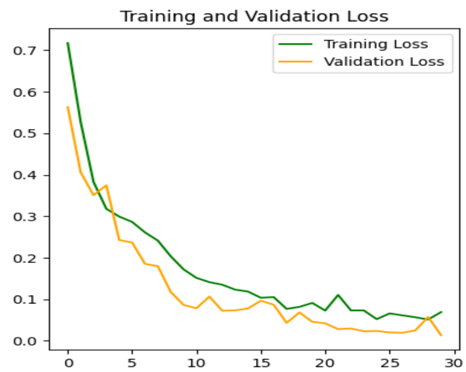
$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision \times Recall} \quad (4)$$

RESULTS AND DISCUSSION

This study compared the performance of four classification models: VGG-16, VGG-19, a Sequential CNN, and a Sequential CNN with a modified learning rate. All models were subjected to the same training and validation procedures, which are summarized in Figure 3. The Sequential CNN models were trained for 30 epochs, providing a more extended learning phase, while the pre-trained VGG-16 and VGG-19 were limited to 15 epochs. This adjustment was made to balance accuracy with computational efficiency, as pre-trained architectures demand significantly more processing power compared to custom-built sequential models. The results are visualized through accuracy and loss curves, where the red and blue lines illustrate training and validation accuracy, and the green and yellow lines display training and validation loss. For clarity, Figures 3(a) and 3(b) show the performance of the basic Sequential CNN, while Figures 3(c) and 3(d) highlight the Sequential CNN with learning rate optimization. Similarly, Figures 3(e) and 3(f) present the accuracy and loss curves of VGG-16, and Figures 3(g) and 3(h) show the corresponding results for VGG-19. These comparisons provide insights into how training duration and model complexity influence classification performance.



(a) Sequential CNN Training & Validation Accuracy



(b) Sequential CNN Training & Validation Loss

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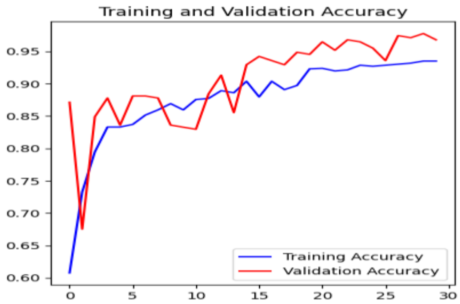
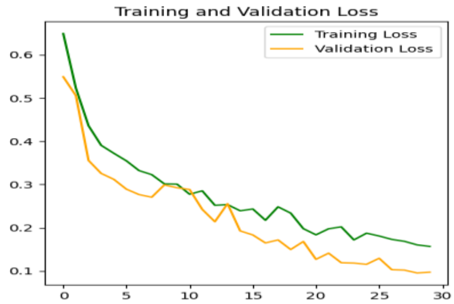
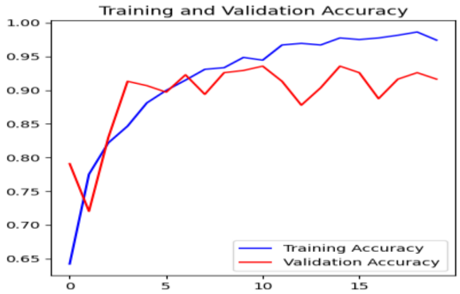
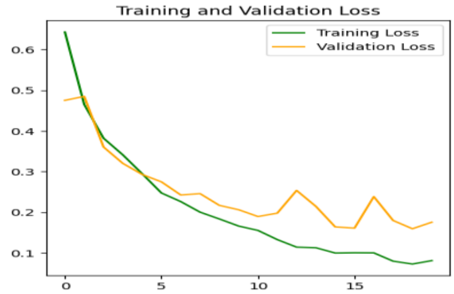


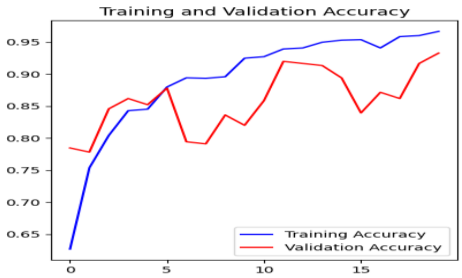


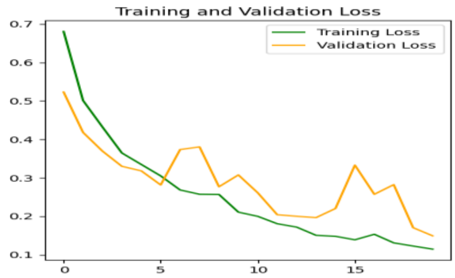
(c) CNN Learning Rate Training & Validation Accuracy (d) CNN Learning Rate Training & Validation Loss





(e) VGG-16 Training & Validation Accuracy (f) VGG-16 Training & Validation Loss





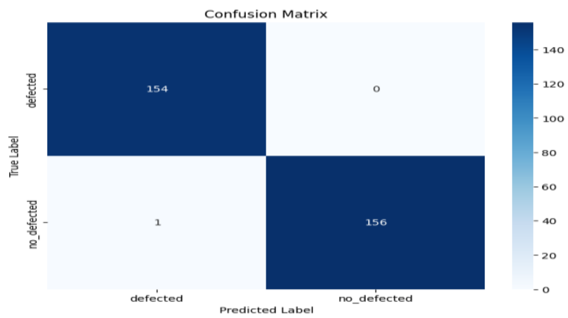
(g) VGG-19 Training & Validation Accuracy (h) VGG-19 Training & Validation Loss

Source : (Research Results, 2025)

Figure 3. Training and Validation All Model Simulation Architecture

The Sequential CNN model performed best in training, validation, and accuracy. Although the values fluctuated slightly, these results confirm that the Sequential CNN model performs well in generalizing 3D printing defect classification.

Confusion Matrix Results



Source : (Research Results, 2025)

Figure 4. Confusion Matrix CNN Sequential

As seen in Figure 4, the confusion matrix of the results of testing the CNN Sequential model on the defected and non-defected classification datasets is shown. Based on the confusion matrix, it is known that the model produces True Positive (TP): 154 defected data were successfully predicted correctly as defected. False Negative (FN): 0 defected data were incorrectly predicted as no_defected. False Positive (FP): 1 no_defected data were incorrectly predicted as defected. True Negative (TN): 156 no_defected data were successfully predicted correctly as no_defected.

Meanwhile, in Figure 5, namely Sequential CNN using learning rate, the prediction results obtained are TP: 153 defected data were predicted correctly as defected, FN: 1 defected data was predicted incorrectly as no_defected. FP: 2 no_defected data were predicted incorrectly as defected. TN: 155 no_defected data were predicted correctly as no_defected.

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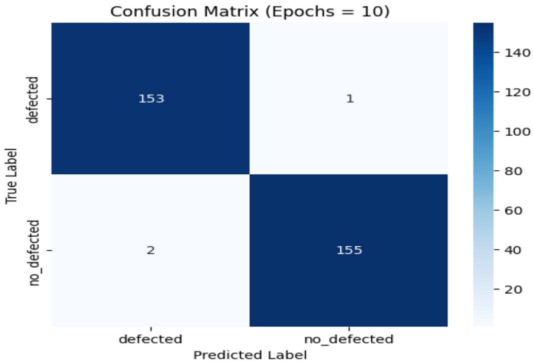
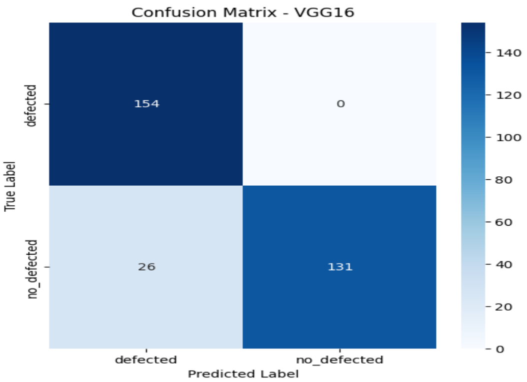
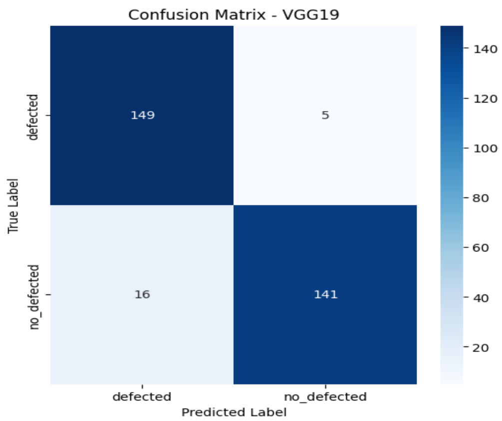


Source : (Research Results, 2025)
Figure 5. Confusion Matrix CNN Sequential with learning rate



Source : (Research Results, 2025)
Figure 6. Confusion Matrix VGG-16

Figure 6 shows the confusion matrix of the VGG16 model testing results. The prediction results obtained are TP: 154 defected data were correctly predicted as defected. False Negative FN: 0 defected data were incorrectly predicted as no_defected. FP: 26 no_defected data were incorrectly predicted as defected, and TN: 131 no_defected data were correctly predicted as no_defected.



Source : (Research Results, 2025)
Figure 7. Confusion Matrix VGG-19

Figure 7 displays the VGG19 confusion matrix with the results, where TP: 149 defective data were correctly predicted as defective. FN=5 defective data were incorrectly predicted as no_defected. Then FP=16 no_defective data were incorrectly predicted as defective. TN=141 no_defective data were correctly predicted as no_defected.

Table 3. Compare with All Model Architecture

No	Model	Accuracy	Precision	Recall	F1-Score
1	Seq. CNN	99.68%	99.10%	99.35%	99.68%
2	Seq. CNN Lear. Rate	98.72%	99.35%	98.08%	98.80%
3	VGG-16	91.64%	92.30%	85.56%	92.22%
4	VGG-19	93.25%	96.75%	90.30%	93.42%

Source : (Research Results, 2025)

As shown in Table 3, the Sequential CNN model achieved the best performance with 99.68% accuracy, outperforming the model with an adjusted learning rate and the pre-trained models VGG16 and VGG19. In addition to accuracy, this model also achieved 99.10% precision, 99.35% recall, and 99.68% F1-score, indicating a high balance between the ability to correctly detect and predict classes. These results show that Sequential CNN is not only accurate but also consistent in recognizing data patterns across all evaluation metrics. The best accuracy results obtained in this study were compared with other additive manufacturing classifications. The approach used was to compare the machine type, material, and computational model used, as shown in Table 4.

Table 4. Compare with Research Additive Manufacturing

No	Research	Machine	Material	Model	Accuracy
1	Kumar *et al.* [21]	3D Printer	PLA	CNN	94.00%
2	Mawardi *et al.* [22]	3D Food Printer	Chocolate	ResNet	93.83%
3	Yusoff *et al.*[23]	3D Printer	adsorbent	CNN Alexnet	96.70%
4	Proposed Method	3D Printer	PLA, ABS	CNN Seq.	99.68%

Source : (Research Results, 2025)

CONCLUSION

Based on the research that has been conducted on 4 models for the classification of 3D Printing defective objects made of PLA materials. With an accuracy rating of 99.68%, it can be said

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that the Sequential CNN model produced the best results. Data augmentation carried out, such as flip, zoom, and rotation, greatly affects the training and validation process. This also shows that the Sequential CNN still has the best performance for 3D printing classification. This study also proves that the type of object greatly influences the model applied. The 3D printing dataset has a dynamic level of data change depending on the printing process carried out. In future research, it is hoped that this model will continue to be developed to be able to perform other classifications on other additive manufacturing, such as 3D printing with multi-nozzle machines, multi-materials, and others. This model should also be validated using real printing datasets from other studies to reflect different data characteristics.

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