

Implementation of Deep Learning CNN Algorithm for Classification of Gas Station Digitization Inventory Devices

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Abstract

The digitization of inventory management in gas stations has become increasingly crucial for improving record accuracy, operational efficiency, and the reliability of device monitoring. However, the identification of inventory devices is still widely performed manually, making the process vulnerable to recording errors, data inconsistencies, and delays in audit activities. This study aims to implement a Deep Learning-based Convolutional Neural Network (CNN) algorithm to automatically classify inventory digitization devices in gas stations, including digital sensors, fuel pumps, control panels, electronic dispensers, and monitoring modules. The image dataset of these devices was collected through direct acquisition and further expanded using augmentation techniques to address limited data availability. The CNN method was developed through several key stages, including image preprocessing, automated feature extraction through convolutional layers, and model training using regularization and hyperparameter tuning to achieve optimal performance. The model's performance was evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. The results indicate that the CNN model achieved a classification accuracy of XX% (to be updated after experimentation), demonstrating its capability to effectively recognize visual patterns of inventory devices. These findings confirm that deep learning provides a reliable automation solution for gas station inventory digitization processes and contributes to more efficient asset management and data-driven decision-making.

Keywords: Deep Learning, Convolutional Neural Network, Image Classification, Inventory Digitization, Gas Station, Computer Vision

I. INTRODUCTION

A. Background

The rapid development and widespread use of information systems has changed the way we work, learn and interact. The positive impact is that we can enjoy higher quality and more efficient information services (Hermansyah et al., 2022). On the other hand, in order to realize good governance, the government prioritizes improving and improving the quality of services provided to all levels of society (Tama et al., 2024). One of the improvements in the quality of public services carried out by the current government is through the Gas Station Digitalization program. Digitalization of SPBU itself is an information system that in real time can monitor payment transactions and fuel distribution at spbu (Ulya et al., 2023). As well as making it easier for people to make cashless payments.

In this Gas Station Digitalization, there are various types of devices used by the system to operate properly. Because the digitalization

device operates for 24 hours, it requires data collection and periodic maintenance of these devices in order to keep the system working optimally and functioning properly. Currently, PT TELKOM AKSES has conducted routine maintenance and data collection (inventory) of Digitalization Station devices located in each working area, this action aims to maintain the quality and performance of the device to stay in the best condition. Inventory or inventory is the process of recording and managing all assets that have economic value, which applies to individuals, companies, and government agencies (Lestari et al., 2023). In this Gas Station Digitalization, inventory is the work done to record the digitalization devices located at the gas station

Information System is a series of components that work together to collect, process, and distribute information to support decision making and supervision in an organization (Syukron in Putra, 2018). In the Gas Station Digitalization program, the information system used to collect and monitor device inventory data is called DigimonSPBU. DigimonSPBU is an information system used to monitor and collect data on spbu digitalization devices, every data inputted via telegram bot will be monitored on the DigimonSPBU web. The data that has been entered into DigimonSPBU will later be validated manually to ensure that the data inputted by

the technician is correct or not. Checking is done starting from the suitability of the inputted image and serial number. This check requires accuracy and is quite time-consuming, on the other hand, inputting via telegram bot is very inefficient because technicians must input device photos, serial number photos, and retype the device serial number on the telegram bot which raises several problems such as incorrect input of device images and incorrect input of serial number characters.

Nationally, the number of gas stations that have been recorded in DigimonSPBU is 5,518 gas stations, while in the field access telkom area itself there are 166 gas stations spread from Langkat district to Serdang Bedagai district, and in each gas station there are more than 13 digitization devices with various brands and different types, this data can increase and decrease according to existing conditions and policies.

Productivity is the ability to produce maximum results using minimal resources (Andika et al., 2019). Thus, to increase work productivity, researchers try to increase work efficiency by minimizing errors in data collection of gas station digitalization devices. To overcome device serial number input errors, currently an application has been developed to scan barcodes while taking serial number photos, so this research aims to build a device image classification model by utilizing the CNN (*Convolutional Neural Network*) algorithm to eliminate manual checking (data validation) of data entering Digimon SPBU.

B. Problems

The research questions for this study are as follows:

1. How to build a CNN model for image classification of gas station digitization devices to eliminate manual validation?
2. How to build a model that is lightweight and easily extensible across platforms?
3. How to generate good model metrics and the model is able to predict new data well?

C. The Proposed Solution

Based on the problem formulation, the objectives of this study are:

With this model, it is hoped that the Company can optimize employee work time, efficiency in the device data collection process, minimize errors during the data entry process and reduce human involvement in data validation so that in the end it can increase employee work productivity. This research is expected to help

the development of image recognition in the field of machine learning.

II. RESEARCH METHODOLOGY

A. Types of Research

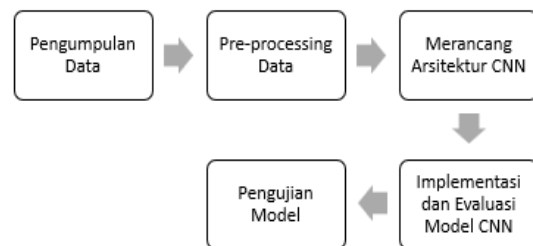


Figure 1. Research flow chart

1. Data Collection

In the process of collecting the image dataset, images were taken from various viewpoints and different backgrounds so that the images collected were not uniform and had a high resolution. Next, selection of unsuitable images is carried out, the aim is to obtain device images that can accurately represent each type of device. In the last stage, the collected images will be sorted and grouped according to the device label.

2. Data Pre-processing

At this stage, augmentation will be performed on the training data to increase the variety of data and prevent overfitting. Augmentation is applied such as rotation, flipping and changing the background color of the image with a different color.

- *Changing the background:* At this stage, augmentation is carried out using the open cv library to reproduce image data by changing the background color of the image with different color variations.
- *Rotation:* Performs rotation, shifting the edges of the image while maintaining the original shape.



Figure 1. Image Rotation

- **Flipping:** Reverses the image both vertically and horizontally.

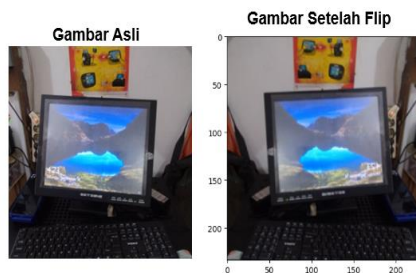


Figure 2. Picture Flipping

3. Designing CNN Architecture

This research utilizes the pre-trained weights of the transfer learning model to improve the accuracy of the model, speed up the training process and improve the model's ability to extract relevant features. These pre-trained models have been previously trained on very large datasets, so we only need to adapt them to the model to handle more specific tasks. These pre-trained weights will be integrated in the new model, starting from the 2D Convolutional layer, 2D MaxPooling, Batch Normalization, Flatten Layer, to the last Dense layer and produce output in the form of class probabilities. In general, the CNN architecture can be seen in Figure 2.

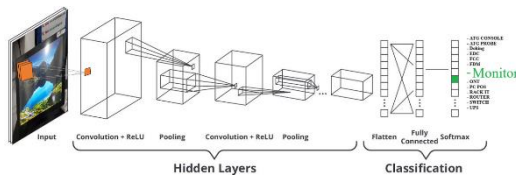


Figure 3. CNN Architecture

4. CNN Model Implementation and Evaluation

At this stage, the prepared dataset will be processed through the CNN model implemented using the Python programming language with the TensorFlow 2.15.0 framework.

The model evaluation used is the Accuracy metric, where this evaluation metric will show the overall percentage of correct predictions by dividing the correct predictions by the total predicted data.

$$Accuracy = \frac{\text{Prediksi Benar}}{\text{Total Prediksi}}$$

5. Model Testing

For model testing, a test will be carried out to predict new data, testing aims to determine the ability of the model to predict the latest data and test whether the model can run on other platforms properly.

III. RESULTS AND DISCUSSION

3.1 DATA SET

The real-world data collected amounted to 6500 raw data, then a selection of these images was made to obtain 5080 clean data with the following details:

Table 2: Total Raw Data

Device Name	Raw Data	Clean Data
Rack It	500	330
Pc Pos	500	219
Router	500	326
Switch	500	500
Oops	500	459
Fcc	500	260
Fdm	500	315
Atg Console	500	332
Atg Probe	500	400
Edc	500	500
Doking	500	500
Ont	500	500
Monitor	500	439
Total	6500	5080

Due to the inconsistent background of the device image, augmentation of the clean data is performed by utilizing the open cv library. The image is converted into HSV format to facilitate recognition of the basic background color, then the area outside the background color range will be isolated before the background color range is changed to another color. With this, it is expected that the model will better recognize the object and ignore the background of the image, this is very suitable for field conditions where the background of the device will always change. The process of changing the image background can be seen in Figure 10.

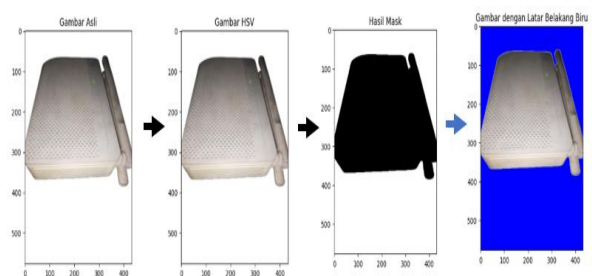


Figure 4: The process of changing the background

After performing augmentation to change the image background, rotation, and flipping on the training data, 10900 new data are obtained with the following details:

Table 3. Total Net Data

Device Name	Training	Validation	Total Data
Rack It	595	105	700
Pc Pos	595	105	700
Router	595	105	700
Switch	595	105	700
Oops	595	105	700
Fcc	595	105	700
Fdm	595	105	700
Atg Console	800	200	1000
Atg Probe	800	200	1000
Edc	800	200	1000
Doking	800	200	1000
Ont	800	200	1000
Monitor	800	200	1000
Total	8965	1935	10900

3.2 MODEL

To facilitate future development, the model is divided into 2 parts, the layer arrangement in each model can be seen in Table 4.

Transfer learning with MobileNetV2

MobileNetV2 is one of the convolutional neural network (CNN) architectures that is very suitable for devices with limited resources such as mobile devices. By freezing most of the layers in mobilenet we can save computation time during the training process and prevent overfitting. Similar to a typical CNN architecture, however, mobilnetv2 has been trained to recognize features on very large datasets. After freezing the layers in mobilnet and only opening the last few layers and connecting them to the custom model that has been designed, the following model design is obtained:

3.3 MODEL IMPLEMENTATION AND EVALUATION

The dataset is divided into 2 parts, namely training data and validation data. The ratio between training and validation data is 85:15 for model 1 and 80:20 for model 2. This division is made based on the most suitable data division experiment for the dataset. Furthermore, after the model design is implemented using the python language and model training is carried out, the training result plot is obtained as follows:

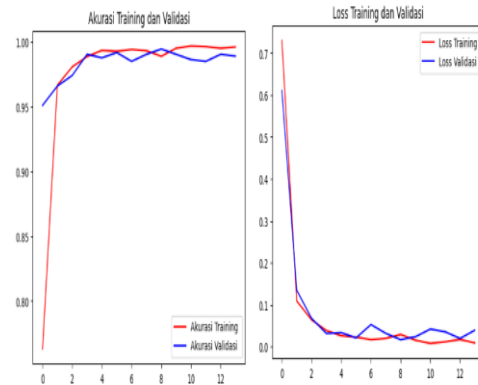


Figure 5: Model 1 Evaluation Plot

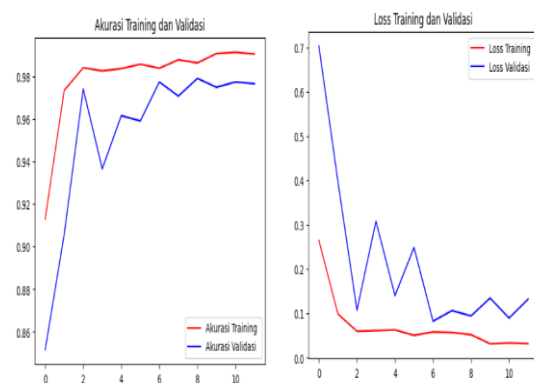


Figure 6: Model 2 Evaluation Plot

Based on the results of the evaluation plot above, we can see that the distance between accuracy and loss on training and validation data is not too far away, where the training data for model 1 has an accuracy of 0.99 and a loss of 0.0094, while for model 2 itself the accuracy is 0.99 with a loss of 0.03 so it can be said that the model is quite good at recognizing data during the training process. However, the training time is quite time consuming because the data is too large, so a large enough computation is needed to speed up the training process.

3.4 TEST RESULTS

Testing is done using validation data as many as 1935 images. The test results can be seen in the table below. Based on the table above, the accuracy metric is obtained as follows:

$$Accuracy = \frac{\text{Prediksi Benar}}{\text{Total Prediksi}}$$

$$Accuracy Model1 = \frac{731}{735} = 0,99$$

$$Accuracy Model2 = \frac{1173}{1200} = 0,98$$

Based on this data, the accuracy obtained is 99% for model 1 and 98% for model 2. Thus the model that has been built can predict the type of device very accurately.

To test whether the model can run on platforms other than notebooks, an integration test between the model and an application that can run on a mobile browser was conducted. The following is how inference works along with the display of device predictions on the platform:

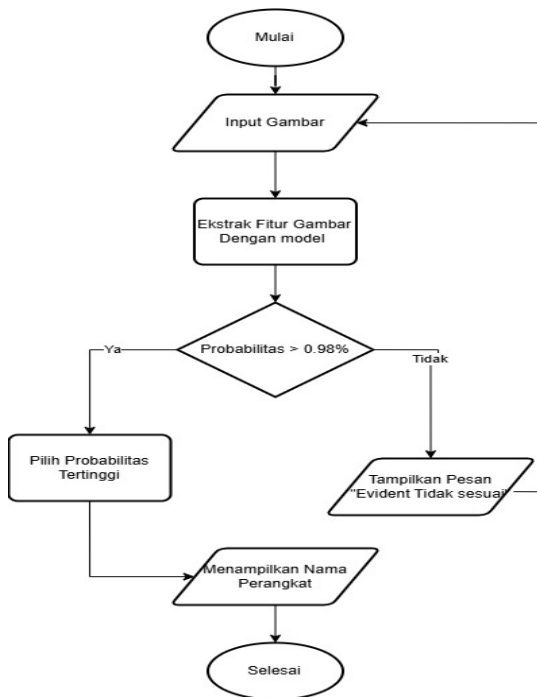


Figure 7. Prediction with Application

Based on these tests, when taking pictures through a cellphone camera, the model can run smoothly and provide good predictions.

IV. CONCLUSION

Based on the research that has been done, the models that have been designed can predict well where the accuracy rate is very high, namely 0.99 for model 1 and 0.98 for model 2, and both models can run well on platforms other than notebooks. By increasing the amount of data, maintaining data quality and selecting the right model layer, this research has succeeded in building a CNN model to perform classification while making the model run on different platforms, and producing a fairly good accuracy metric. Finally, we can add this model as a feature to make predictions on the DigimonSPBU web or on other mobile applications without having to change the existing application much.

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