Product Identification System Design Based on Deep Learning

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Abstract
Product identification approach has become a crucial issue for the inventory monitoring process. Because of the enhanced product spectrum and many shipment points, it is quite likely to send incorrect orders to the customer erroneously. With the help of this proposed model, particular troubles during product shipment could be solved.

In this study, it is aimed to not only delivery right product to the right consumers but also ensures Kanban system inside the facility by performing product identification procedure. Within the scope of this study, a technology - industry integrated system has been designed by using convolutional neural network architecture.

Keywords: Convolutional Neural Network, Deep Learning, Product Identification

1. Introduction

Recent developments in the field of computer hardware have resulted in huge progress in Artificial Intelligence (AI) technology. The reason behind this fact that complex and complicated problems could be handled within a short amount of time with the help of high computer technology. Thus, the AI method not only could be more efficient to make comprehensively analyses and find more accurate outcomes but also has gained a novel structure to perform dynamically. Conventional AI methods take into whole problem steps into consideration to create a unique model. Different from the classic AI model, dynamic AI techniques try to find the most suitable model parts for each sub-level of case studies (Torkul et. al., 2017). At this point, deep learning concepts include this dynamic framework which is able to generate compact solutions for pre-defined small models. In order to increase understanding of deep learning logic deeply it is possible to state that in the deep learning, each neuron of network concentrate on a specific part of the problem, so more accurate results could be obtained by deep learning architecture in which even small details could be realized.

2. Literature Review

There has been an increasing amount of literature on deep learning concepts. (W. Liu et al., 2017) has published a comprehensive paper in order to summarize available studies based on four basic deep neural network architectures with their application areas. Generally, deep learning studies are accumulating on the area of face and object recognition. At this point, some examples can be given to prove this claim. Studies on expression detection in videos, (Gupta, Raviv, & Raskar, 2018) can be given as a significant research. On the other hand for malicious software realization process (J. Y. Kim, Bu, & Cho, 2018) could be suggested. Besides, Pixel–level fusion (Y. Liu et al., 2018) study can be acceptable to understand theoretical and practical applications.

It is so clear that deep learning architecture could apply for the benefit of many distinguished areas such as biological, ecological, chemical, social and manufacturing fields. In order to exemplify this fact some studies from different sectors are mentioned below.

(Yildirim, Tan, & Acharya, 2018) created a new deep convolutional auto-encoder model for the health sector. They claimed that during electrocardiogram signals comprising, the main issue is to ensure an accurate data transmission and it could be possible a deep compression method. Bearing fault diagnosis concept has been analyzed by (Hoang & Kang, 2018) and they have generated an organized pattern by using auto-encoder, Restricted Boltzmann Machine and Convolutional Neural Network application of essential deep learning algorithm. Ultimately, hand-craft ability, knowledge, and quality of labor parameters are figured out as the necessary features to get high-performance rate. (Na, Jeon, & Lee, 2018) investigated gas dispersion model in the chemical industry using an integrated model which is a combination of a surrogate model and deep neural network. From the manufacturing aspect, (Maggipinto, Masiero, Beghi, & Susto, 2018) have been offered a method to withdrawal feature from complex and complicate semiconductor industry. Lastly, (Chen et al., 2018) has been embedded DNN in their study to determine facial emotional situations during human and other autonomous robots integration.

3. Theoretical Background

During thinking and problem solving, the human brain performs a large number of automatic actions. These processes are usually classification (anomaly detection, object recognition, and face recognition, etc.), clustering, estimation, optimization, simulation, inference engine. In order for an artificial intelligence system to solve problems, it must have mechanisms to carry out the above processes. In order to create the required structure, a large number of layers can be designed in deep neural networks and specialization of each layer can be achieved. Each layer transmits the inferences of the subject to the next layers. Layers that retrieve data from previous layers produce results using the inputs they receive.

For example, in a system that will recognize the product, a layer can detect the color of the product. Because each color has a large number of tints, the camera will show the color of the product that it has taken, depending on the lighting, but in different tones. Another layer can decide about the size of the product, and a layer can decide on the shape of the product. These decisions are forwarded to a layer; the product can be determined by evaluating the details of the product in the relevant layer. Although the methods of working with deep learning systems are based on the dynamization of artificial neural networks, various deep learning algorithms have been developed for specific problems. In this section, convolutional neural networks, deep belief networks, and deep auto-coders have been investigated (Liu et al., 2017).

3.1 Convolutional Neural Networks

Convolutional neural networks have been developed for the first time (LeCun, Bottou, Bengio, & Haffner, 1998) and are now available in many areas. Convolutional neural networks are a type of multilayer feed-forward neural networks and consist of many convolutional integrating layers. Convolutional neural networks have a common feature with the artificial neural network in terms of features such as weight assignments and error calculations. Therefore, the convolutional neural networks do not require fully dependent layers and can also be specialized for different tasks with hidden layers (Deng, 2014).

3.2 Deep Belief Networks

Deep belief networks are a probabilistic model trained using the Restricted Boltzmann Machine (RBM) to learn a layer of hidden property at a time (Hinton, Osindero, & Teh, 2006). After the training process of the first layer is completed, the second layer of the hidden units of the RBM is added. The layers are added sequentially until they reach the desired number of layers. The learned properties of the first layer are sent as input for the second layer and the second layer is trained in the same manner. Nowadays, deep belief networks are used less frequently than unsupervised or generative learning algorithms, but they are still defined within the scope of deep learning.

3.3 Deep Auto-Encoders

Auto-coders are defined as simple neural networks that can be used for unsupervised learning (Rumelhart, Hinton, & Williams, 2013). The most important feature of the auto-encoders is that they attempt to set the output values equal to the input values. The number of output neurons is the same as the inputs, but the number of hidden neurons is different. Thus, the input data is expressed by a different number of units. The weight values of these hidden neurons are determined using the backpropagation algorithm. An auto-coder is an artificial neural network model that aims to reconfigure its own inputs. Therefore, it is also used for cases of reducing when the number of hidden units is less than a number of input units.

4. Deep Learning Application Structure

In addition to the techniques used in artificial neural networks, some new methods have been developed in deep neural networks for the correct operation of the network and in order to avoid the memorization in artificial neural networks. These developed methods enable the dynamic operation of deep networks and the concentration of layers on different jobs. This dynamic structure of deep networks is the most important feature that separates from the artificial neural networks that analyze each data with the same model. Therefore, methods developed specifically for deep networks aim to run the data-specific layers to be analyzed instead of running all layers of the network at the same time.

Since deep learning systems are a specialized type of artificial neural network, some traditional problems in artificial neural networks are also present in these systems. One of the most common problems encountered is the overfitting problem. During the training process of the data set, this phenomenon, called overfitting, occurs because the error approaches the zero after a certain stage as the training steps progress. Another problem encountered is the under-fitting status. This problem is due to poor training conditions.

The design of the deep neural network is similar to the artificial neural network design. As in the artificial neural network, hidden layers, activation functions, learning algorithms, loss functions, learning coefficient such as hyper-parameters are used. These hyper-parameters are formed by the addition of hyper-parameters such as integration, convolution, auto-encoder layers, and dropout. While new hyper-parameters are used in the training and practicing of deep networks, the training process of deep networks and artificial neural networks is similar. Similar studies are carried out to prevent overfitting and under-fitting problems during training. In this section, the studies in the training process and the hyper-parameters are examined under four topics. These are convolution, pooling, early stopping and dropout explained in depth as follows.

4.1. Convolution

Convolution layer generates new images which are called feature map ((Lecun, Bengio, & Hinton, 2015). This map emphasizes the unmatched properties of the master copy of the image. If convolution layer is compared with other neural network layers, it is obvious to claim that it performs completely different by utilizing particular filters which are able to convert images instead of weights or relations.

4.2. Pooling

Pooling process is utilized to decrease spatial dimensions by protecting valuable information. It is located at the end of the convolutional layer. It is crucial to determine which pixel should be selected and how to define representation value during the pooling process.

4.3. Early Stopping

During data training, training error is decreasing in the course of time consistently however, test error starts to decrease after a specific point. This situation is called overfitting mentioned above. In order to regulate this kind of unwanted situation, the early stopping technique has been widely used. The reason behind its popularity is not only its efficiency but also it could be applying in an easy way. (Good- fellow, Benğio, & Courville, 2017)

4.4. Dropout

Dropout method is also preferred by both academicians and practitioners in an attempt to prevent the under-fitting problem. In this layer, some nodes with their input and output relations are detected and eliminated. Because of this procedure, the possibility of the under-fitting problem could be solved before it happens.

5. Product Identification Model & Application

Identifying the product (Auto-ID) technology is a new approach to inventory transaction monitoring. It allows decreasing the cost of monitoring and provides a full-control of the equipment shipped. Thus, Auto-ID systems prevent misdeliveries. A novel convolutional neural network (CNN) model has been proposed to perform the function of the Auto-ID system. CNN has two convolutions and pooling layers. Convolution layers infer 32 and 64 features with the core parameter 4. Because products have different color features, RGB data is evaluated in the network. Product images shown in Figure 1 are transformed into 48x27x3 sized arrays to employ the network faster and evaluate the color of products more accurate.

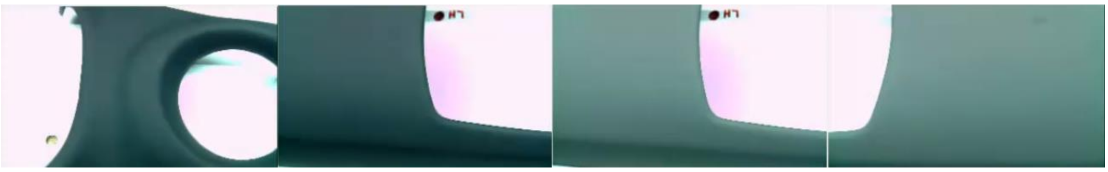

Figure 1: Products Images (Torkul et al., 2017)

After Relu activation in the first layer, outputs are classified with an A* heuristic, which grabs the image of the product from a background as seen in Figure 2. Background pixels are set to 0 to eliminate before passing data to the second layer. Pooling layers provide cleaning gloves and shadows at the edge points, and 2D convolution layers are expected to learn color and shape of the product. A dense layer having 1024 nodes is set with 25% dropout ratio to prevent the network from overfitting. Because small images are used, high dropout ratio is set for the layer. Finally, a logit layer is added to the model to detect 17 products.

Figure 2: Grabbing the product from the image (Torkul et al., 2017)

Training of the network takes 2000 steps and softmax cross entropy is used as a loss function to increase classification performance. Loss rate during the training is given in Figure 3. Small-scaled 51 images of products enable a short training period as 15 minutes in a notebook having i7 processor and 12 GB memory. The test set is classified with the 99.008% of R2, which is consisted of 15 images grabbed with the same camera in same conditions.

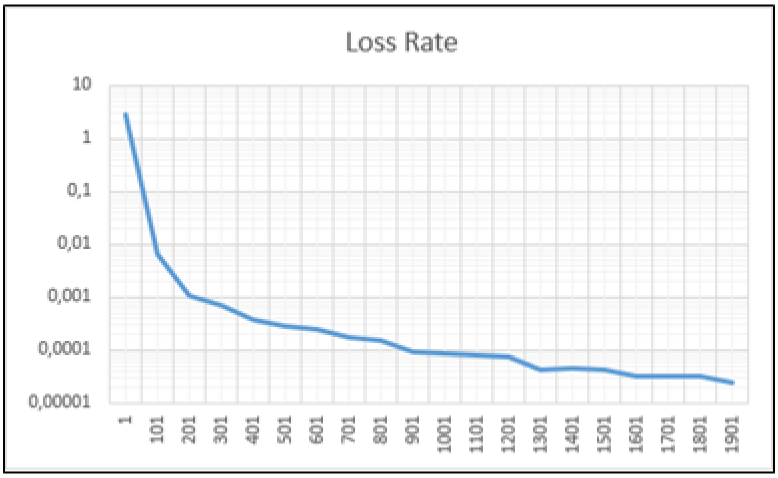

Figure 3: Loss rate of training

6. Conclusion

Auto-ID technology eliminates barcode and RFID systems in the industry, by decreasing monitoring cost and increasing flexibility. Because the Auto-ID system knows the product, it can easily detect any anomalies on the product as any barcode or RFID system cannot. One of the efficient ways of developing an Auto-ID system is to utilize the deep neural network, which is accepted as an efficient classifier. A CNN model is developed in order to detect products from real-time grabbed images for controlling the shipment process. Within the scope of this study, an obvious solution has been proposed for the misdelivery problem.

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