Using Convolutional Neural Networks for Detecting Acrylamide in Biscuit Manufacturing Process

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Abstract: Based on a research in 2002 (Ozkaynak & Ova, 2006), acrylamide substance is formed when excessive heat treatment (e.g. frying, grilling, baking) is applied to starch-containing products. This substance contains carcinogenic and neurotoxicological risks for human health. The acrylamide levels are controlled by random laboratory sampling. This control processes which are executed by humans, cause a prolonged and error prone process. In this study, we offer a Convolutional Neural Network (CNN) model, which provides acceptable precision and recall rates for detecting acrylamide in biscuit manufacturing process.

1 INTRODUCTION

In the food industry, the acrylamide substance can be found in the final products due to the exposure of carbohydrate-containing foods to excessive heat (Ozkaynak & Ova, 2006). This substance is understood to have carcinogenic effects on humans; therefore, it must not be consumed.

Providing healthier products to our customers and maintaining their trust is vital. The solution we designed guarantees us that every product that we will be producing is under control and they can be safely consumed. This way, production efficiency can be maintained in terms of time, waste and cost.

Before developing our solution, the initial solution method was twofold:

1. Random sample parties are selected from the products to detect the number of products containing acrylamide levels two times a year
2. Eye control to detect color change is executed during production.

We collected the product photos that contains acrylamide above and belove the accepted levels to build a dataset. Normalization and resizing operations are also planned to be used to make this data set suitable in the future. After creating the dataset, data manipulation is performed by changing brightness, rotation, scrolling, etc. We shaped the model by optimizing the parameters to provide better recognition accuracy. We performed data augmentation by using the model features. After we created enough data for the model to learn, we started to build our model. After training the model with the data that we split into train and test partitions, we tested our model in the quality control process.

By solving our problem using the image processing method, we eliminated the risk of overlooking inefficiency by avoiding manual control. Control process is also automated by using the cameras. Since it is not controlled by people, the speed of the production line is also increased. This algorithm can be used for the quality control processes of other products or to measure the amount of acrylamide levels in similar products.

2 MATERIAL AND METHODS

Detection of acrylamide is one of the most considerable problem for each company producing carbohydrate-containing foods. Therefore, the solution to this problem is also important. By referencing the literature, we tried to develop a solution to determine acrylamide in consumed foods by using different methods.

In the model that is used to detect acrylamide in potato chips, BatchNormalization() is used to prevent

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the model from overfitting. This function, brings high success to prevent overfitting in image processing, also provided successful results here. For this reason, we used BatchNormalization() to suppress overfitting in our model. Moreover, U-Net was used to classify images of potato chips. The data we used in our model was split as train, validation and test. Sigmoid is one of the suitable function as activation for the output layer of the model; since, it returns a value between 0 & 1. Another process is the normalization step of the data set. Due to the data volume, algorithm execution time should also be considered. For this reason, we arranged the photos by the highest number of pixels (255). Thus we made them more comfortable to process in the [0,1] range. In the article (Maurya et al., 2021), the transfer learning method is used while constructing the model. Transfer learning is a machine learning methodology that focuses on storing the knowledge gained while solving a problem and applying it to another similar problem (Yiğit & Yeğin, 2020). We wanted to use unique methods in our model to stay flexible to dynamic business requirements, so we did not choose to use pre-trained models.

The article (Arora, M. & Mangipudi, P. & Dutta, M. K. 2020) studied the amount of acrylamide in potato chips, which is the study (Maurya et al., 2021), also investigated. In this approach, they used a pre-trained model and obtained a high model accuracy.

In this article, Acrylamide is detected in potato chips with the help of LC-MS Analysis. Liquid Chromatography with Tandem Mass Spectrometry (LC-MS-MS) is a powerful analytical technique that combines the separating power of liquid chromatography with the highly sensitive and selective mass analysis capability of triple quadrupole mass spectrometry (EAG Laboratories, n.d.) This method is checking whether it contains acrylamide by looking at the distribution of colors on the chips. We did not try this method as it would not help in accelerating our process in line with our targeted outputs (Gökmen et al., 2007).

In this approach, they tried to reach the result with the help of chemical studies. We did not use this solution method here due to its distance from our targets and work area (Alpözen et al., 2013).

In the light of the information obtained as a result of the literature review, the Acrylamide substance was not detected by image processing with the CNN algorithms, which was specifically trained for Acrylamide substance. Therefore, we wanted build our own model architecture from scratch.

3 EXPERIMENTS

We collected and assorted the photos of the products taken by the business unit. Overall, we have 572 pictures; 201 of them are above the threshold (meaning they consist acrylamide greater than the threshold), 371 of them are below the threshold (meaning they do not consist acrylamide greater than the thresholds) (see Figure 1 & 2).

Figure 1: A sample above the threshold (label as acrylamide).

Figure 2: A sample below the threshold (label as non-acrylamide).

We split our data set into test & train data sets; for training we used 160 pictures and for testing we used 40 pictures from both above and below datasets. After the split process, we set data to 224x280. We used this data to train and test the Convolutional Neural Network model.

3.1 Creating the Model

There are five convolution layers in total in the Convolutional Neural Network model that we designed.

The kernel size of the first four layers was 3x3, and the last layer's kernel was 1x1. After each convolution layer, there was a Batch Normalization layer.

We spread an effort to reduce the data size. Therefore, we used MaxPooling in size 2x2 after the first four convolutional layers. After the last convolution layer, we transformed the data into one-dimensional tensor by flattening. This one-dimensional tensor was given as an input to the fully connected layers.

Our model had six fully connected layers. The first five fully connected layers contain 128, 64, 32, 16, 10 neurons, and the fully connected output layer contains 1 neuron.

To prevent over-fitting, dropout layers were used after convolution and fully connected layers.

For the cross-validation method, we created 5 different data partitions by dividing the data into random groups. All groups were set to contain an equal amount of data. We used 80% of the data for training and 20% for testing. Batch Size was set to 1 to allow more accurate gradient value calculation and to reduce linearity.

We trained the Convolutional Neural Network model with Adam optimizer at 100 epochs and set the initial learning rate to 0.0001.

The loss function was chosen as the binary cross-entropy, which provided the best binary classification result.

After training the model, we sent the test data to the model and classified the predicted label value by comparing it with the values found as a result of the *sigmoid* function.

All operations were executed on NVIDIA GeForce GTX 1080 Ti workstation with 64GB RAM. Rescaled using MATLAB 2020b, classification was performed using Python 3.9.7 and Keras 2.8.0 (using Tensorflow 2.8.0 backend).

3.2 Data Augmentation

Since the data set we have was not enough for the model to learn completely, the data was replicated with the help of the ImageDataGenerator() function. In this step, our train and test data;

- By specifying the rotation_range parameter, which rotates the image randomly clockwise by the given degree (40 degrees),
- By specifying the rescale parameter 1./255, which performs the normalization process,
- By specifying the zoom_range parameter 0.2, which is used to zoom the image,
- By specifying the shear_range parameter 0.2, which distorts the image in the axis direction,
- To move the image horizontally, by specifying the width_shift_range parameter to 0.2,
- To move the image vertically, by setting the height_shift_range parameter to 0.2,
- Set the horizontal_flip parameter to True to flip the image horizontally.

were multiplied. As a result, we obtained 5 new pictures from each training picture. In the end, we had 800 pictures for both above and below threshold classes.

After reshaping the dimensions of our data, the learning process was carried out by fitting our model. We calculated our success metric "accuracy" which is the number of correct predictions/total number of predictions. Although accuracy was our main evaluation metric, evaluating it alone was not the right approach. We also used Precision and Recall metrics to better observe the reliability of Accuracy. The precision tells us how many of the positively predicted class predictions are essentially positive. In other words, it refers to the formula TP/(TP+FP). Recall, on the other hand, gives the ratio of how many of the transactions we need to predict positively are essentially positively predicted. In other words, it is formulated as TP / (TP+FN). When we took the average of 5 results, we got 93.25% Accuracy, 88.5% Precision, 98% Recall.

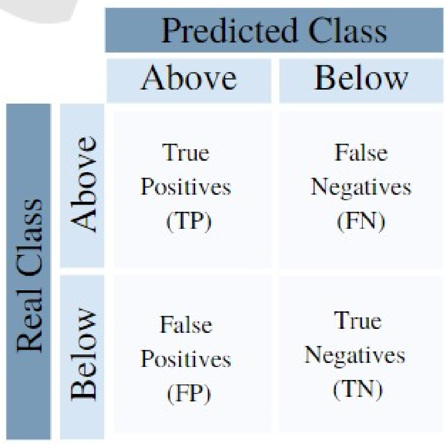

Figure 3: Confusion Matrix Representation.

4 CONCLUSIONS

We predicted the acrylamide levels as belove or above threshold) in our production lane by using image processing with a Convolutional Neural Network model that was specifically built for detecting Acrylamide substances. The results obtained are summarized below.

- Our products can be delivered to consumers with high confidence,
- The old way of detecting acrylamide in the product will not be needed,
- Thus, the product line will progress faster
- Packaging of the products will be faster,
- The risk of detection errors will be reduced as it switches from human control to machine control
- In the future, we are planning to integrate our model into a mobile application to make our solution user friendly.

Table 1: Classification results for five-fold cross-validation using the Convolutional Neural Network model and the total result obtained by adding the folds.

Iterations	Confusion Matrix	Accuracy	Precision	Recall
I	39 1 2 38	96.25%	97.5%	95%
II	39 1 1 39	97.5%	97.5%	97.5%
III	38 2 0 40	97.5%	95%	100%
IV	27 13 0 40	83.75%	67.5%	100%
V	34 6 1 39	91.25%	85%	97.5%
Total	177 23 4 196	93,25	88,5	98

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In Figure 3 *Expressed in this way, "above" stands for Positive, "below" stands for Negative.*

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