Report on Deep Learning System for Quality Control in Glass Bottle Manufacturing

Group G

Introduction:
In the contemporary manufacturing landscape, companies must ensure product quality to sustain competitiveness and meet consumer expectations. Traditional quality assurance methods, particularly in industries like glass bottle manufacturing, involve manual inspection processes that are time-consuming, error-prone, and lack scalability. To address these challenges, LTP Labs, in collaboration with Glass Before Plastic (GBP), embarked on a project to leverage Predictive Analytics and Deep Learning techniques to revolutionize quality control processes in glass bottle production.

Problem Statement:
GBP, a leading glass bottle manufacturer, faced significant challenges in maintaining stringent quality standards across its production lines. Manual inspection methods were inadequate to detect defects accurately and efficiently, leading to potential quality issues and production bottlenecks. Hence, the objective was to develop a deep learning system capable of predicting defects and defect rates in real-time, thereby enhancing quality monitoring and operational efficiency.

Dataset and Features:
The dataset consists of 239320 observations and 239 variables. It is a time series dataset and does not have any missing observations. It consists of sensor measurements collected at the production line. The production line has 10 Sections, and each section consist of 3 cavities.

The column *defects* is obtained from the *defect_rate* where, we have 1 if *defect_rate* is > 0.02 and 0 when *defect_rate* is < 0.02. As a result of this transformation the variables *rejected_Sidewall* and *total_Sidewall* is dropped from the dataset. The variables *reference* and *production* were dropped as they were not needed for the Deep Learning model.

The *features set*, includes all variables except *defect_rate* and *defected*. Additionally, *initial_time* and *final_time* were transformed into 'duration' which gives the total duration in minutes for a batch and then dropped from the dataset.

To test the performance of our model out of batch we created at first a holdout dataset stratified with a 0.2/0.8 split. Due to imbalance in the number of observations of the two classes in *defects*, Up-sampling was incorporated to create a balanced dataset. The changed dataset was then again split into a training and testing dataset with an 0.2/0.8 split, in order to train the models and then test the models between each other. The best performing model was then tested on the not upsampled holdout dataset.

The variables except in the *features set* were assigned target sets for the model.

<u>Approach:</u>
The model architecture comprises a combination of dense neural network layers, including batch normalization and dropout layers, designed to handle the complexity of the input data and extract relevant features for defect prediction. We tested 3 different models, two with different optimizers, which are "adam" and "SGD". The last model used many BatchNormalization layers and used the best performing optimizer.

<u>Model Architecture:</u>
Type of Model: We constructed the model using the Keras Sequential API in TensorFlow which allows for flexible architecture design and multi-output capabilities.

Number of Layers and Units: The base model consists of three dense layers with 256, 128, 64 and 32 units, respectively, followed by a dropout layer for regularization. After every hidden dense layer a BatchNormalization layer was used to improve out of batch performance.

Loss Functions: The model employs mean squared error loss for regression output (*defect_rate* prediction) and categorical cross-entropy loss for classification output (*defects* detection).

Metrics: Evaluation metrics include Mean Squared Error (MSE) for regression output. Accuracy and Area under the curve (AUC) for categorical output, providing comprehensive performance assessment.

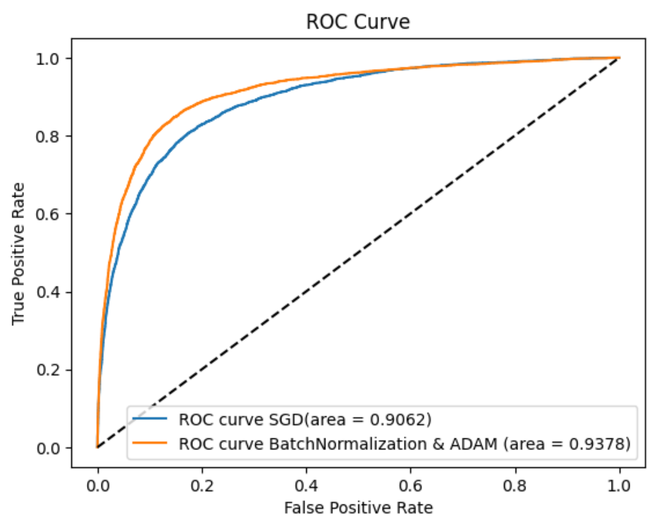
Optimizer: After testing the first two models it turned out that “adams” was the better suited one. It improved the roc_auc metric by 1.8 percent points and accuracy by 1.6 percent points, compared with the model that used “SGD” with a learning rate of 0.001 and a momentum of 0.9. No improvement for the “mse” was noticeable.

Batch Size: Training is conducted with a batch size of 128, balancing computational efficiency and gradient accuracy.

Early Stopping: We implemented early stopping to prevent overfitting by monitoring validation loss and reducing the learning rate on plateaus, ensuring optimal model generalization.

<u>**Evaluation and Conclusion:**</u>

Upon training and evaluation, of the different models it turned out that a model with Batch normalization after every Dense layer and the optimizer “adam”, were the best suited for predicting defects. The BatchNormalization and adam model generated the big improvements, which is seen in the figure to the right. Through the models there was no noticeable improvement to the mse of the regression output, which was unexpected. The deep learning model demonstrates promising performance in predicting *defect_rate* and *defects*. The achieved metrics on the test dataset are as follows:



- Mean Squared Error (MSE) for Regression Output: 0.00053677
- Accuracy for Categorical Output: 86.75%
- Area Under the Curve (AUC) for Categorical Output: 93.78%

These results indicate robust model training and generalization capabilities. Despite the inherent complexities in glass bottle manufacturing processes, the model exhibits competitive accuracy and efficiency in identifying defects and estimating defect rates.

In conclusion, the developed deep learning system presents a viable solution for enhancing quality control and operational efficiency in glass bottle manufacturing. By leveraging Predictive Analytics techniques, GBP can streamline its quality assurance processes, minimize defects, and uphold its reputation for delivering high-quality products to consumers. The model's demonstrated accuracy, AUC, and MSE values underscore its potential to revolutionize quality monitoring practices, offering GBP a sustainable competitive advantage in the industry.