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

Group G - 17.05.2024.

Dataset and Pre-Processing:

For this phase of the project, we continued to use the same dataset collected from the production line, comprising sensor measurements and defect information. Pre-processing steps included transforming defect rates into categorical attributes, dropping irrelevant columns, creating dummy variables for categorical attributes, and normalizing the features using StandardScaler. Furthermore, we created time series datasets out of our data with a batch size of 124 and a sequence length of 50. It uses timeseries_dataset_from_array to convert feature and target arrays into datasets. These datasets are then combined into a single dataset. This is applied to generate training, validation, and holdout datasets from the respective feature and target arrays. This is necessary for running recurrent neural networks.

Model Architecture:

In this iteration, we incorporated Recurrent Neural Networks (RNN) into our model architecture. Therefore, we tested simple RNN, GRU Networks and Long Short-Term Memory Networks (LSTM). The best performing network in our case was the LSTM. Our final implementation comprised two LSTM layers with 64 units each, followed by dropout layers for regularization to prevent overfitting. The model had two output layers: one for regression output defect rate prediction ("perc_defects_Sidewall") and another for classification output defect detection ("Defect").

Results and Evaluation:

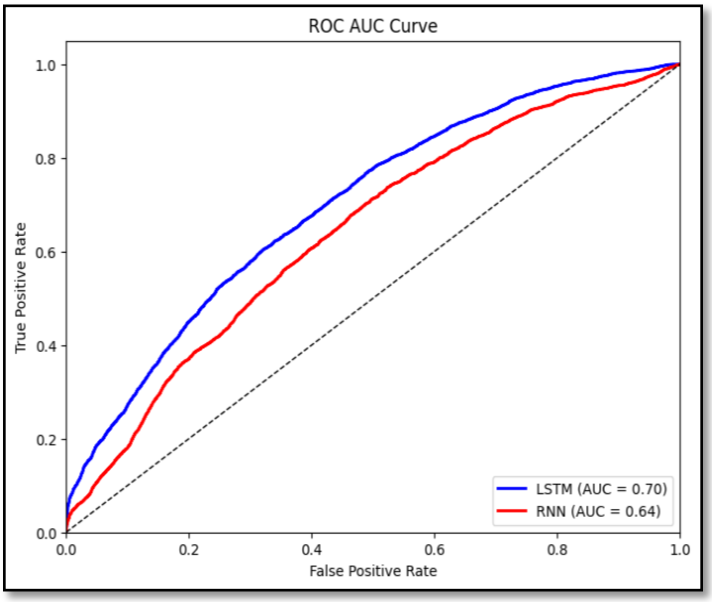
The LSTM model was trained using the *adam* optimizer for 10 epochs on a training dataset, with 80% of the data, and validated on a separate dataset comprising 10% of the data. *Early stopping* was employed to prevent *overfitting*. Upon evaluation, the LSTM model demonstrated promising performance in predicting defect rates and detecting defects.

The achieved metrics on the holdout dataset were as follows:

Mean Squared Error (MSE) for Regression Output: 0.0003185

Accuracy for Categorical Output: 78.46%

Area Under the Curve (AUC) for Categorical Output: 70%



These results indicate the LSTM model's robustness and effectiveness in enhancing quality monitoring practices in glass bottle manufacturing. While the LSTM model shows promising performance, it's noteworthy that the first model submitted during the initial phase of the project remains the better-performing model. However, the incorporation of RNNs, specifically LSTM, still offers GBP a sustainable competitive advantage by providing accurate defect prediction and efficient defect detection, ultimately ensuring high-quality product delivery to consumers.