1. Introduction and Description

In my role at Continental within the Conti-Tires division, the scope of this project fits into the larger framework of tire production and research. Continental is structured into different divisions, including Conti-Tires, Conti-Tech, and Conti-Automotive, and I am part of Conti-Tires. This division oversees the research, production management, and operational tasks necessary for tire manufacturing across several plants worldwide. The ultimate goal is to meet business and customer needs while maintaining high-quality production standards. As part of this project, I'm engaged in business operational tasks, which include creating a machine learning algorithm that predicts scrap generated during tire production. This involves consulting with various production plants and developers to gather input on the factors influencing scrap. My role specifically focuses on Scrap 56, a type of scrap categorized under Scrap IV, which is prevalent during certain stages of production at the Camacari plant. Tire production itself is a complex process involving multiple materials and components, such as rubber, silicon, steel, and textiles. The tire undergoes various stages, starting with the green tire stage (when the tire has not been vulcanized) to the final cured tire, which is ready for use. At each of these stages, several parameters are closely monitored, including the build of materials (BoM), mold contour, pattern, and dimensional specifications. These factors collectively impact the performance and quality of the final product.

Throughout the manufacturing process, various types of scrap can be generated due to deviations in specifications, production flaws, or defects in materials. Continental classifies these scrap types into different categories, for example, Scrap 1, Scrap 2, Scrap 3, and so on, with each category further subdivided into scrap codes. For instance, Scrap IV includes codes such as 01, 01A, 56, and 90A. My project focuses specifically on predicting Scrap 56, which is one of the subcategories under Scrap IV. In terms of the project's technical implementation, I am utilizing historical data on tire production, scrap generation, and various production parameters. The data includes fields like tire article IDs, BoM specifications, mold contour parameters, production duration, and the number of tires produced during that period. The goal is to build a machine learning model, currently a neural network, that uses these inputs to predict the amount of Scrap 56 generated.

Due to the vast amount of data available from multiple plants and different scrap codes, I decided to narrow the project's initial scope. The current model uses data only from the Camacari plant and focuses exclusively on predicting Scrap 56. This provides a manageable starting point for model development and allows me to ensure the model's accuracy and relevance to a specific scrap code and plant. The key technical aspects include feature engineering, data cleaning, and preprocessing, where I normalize data points, handle missing values, and encode categorical variables. Given that the neural network model is sensitive to input scales and data quality, this preprocessing step is crucial. The network's architecture is designed to account for non-linear relationships between the input features (BoM, mold contour, etc.) and the target variable (Scrap 56). Once the model is trained, its performance is evaluated using common metrics like Mean Squared Error (MSE) and R-squared, which measure how well the model predicts scrap quantities. For the project's future direction, the model can be expanded to include additional scrap codes beyond Scrap 56 and incorporate data from other production plants. I plan to benchmark different machine learning algorithms (such as random forests or gradient boosting) to improve prediction accuracy and generalization. The ultimate goal is to create a robust, scalable model capable of predicting all scrap types for any Continental production facility.

1. Project Title: Predictive Modeling of Scrap 56 in Tire Production Using Neural Networks

Project Description

The project aims to develop a predictive model that forecasts the amount of Scrap 56 generated during tire production based on various specifications and production parameters. The input data consists of a range of tire articles (identified by unique IDs) and their associated Build of Materials (BoM), Mold Contour parameters, production duration, and the number of tires produced. The primary objective is to predict the quantity of Scrap 56 generated during serial production for each set of tire specifications, helping to optimize production processes and minimize waste.

The current focus is on data from the Camacari production plant, specifically targeting the prediction of Scrap 56, a type of scrap code categorized under Scrap IV. This project employs a neural network algorithm to model the relationship between the input specifications and the Scrap 56 generated. The model will initially be trained and validated using historical production data from the Camacari plant.

Future Goals and Expansion

Algorithm Expansion: The model can be expanded to include different machine learning algorithms, allowing for benchmarking and accuracy comparisons.
Plant-Wide Application: The model could be scaled to predict scrap for multiple plants beyond the Camacari facility.
Scrap Code Expansion: Extend the model to predict other types of scrap, in addition to Scrap 56, allowing for comprehensive scrap management across the production process.
Real-Time Implementation: Integrate the predictive model into a real-time monitoring system to provide actionable insights during ongoing production.

Advantages of the Project

Waste Reduction: Predictive modeling helps in identifying the factors leading to higher scrap rates, allowing for proactive adjustments in the production process, thereby reducing waste.
Cost Efficiency: By minimizing scrap, the project contributes to significant cost savings in raw materials, energy, and labor.
Process Optimization: Insights from the model enable continuous improvement in tire production processes, leading to better quality control and efficient resource utilization.
Scalability: The model’s architecture allows for easy expansion to other plants and additional scrap codes, making it a versatile tool for the organization.

2. Data Collection and Preparation Overview

In line with the project description and task, I collected data from various sources, including Tableau, Power BI databases, and other relevant data repositories. The goal was to gather comprehensive data related to tire production specifications, scrap rates, and production details to train a predictive model for Scrap 56.

Data Collection

I accessed and extracted data from different servers, where the data was stored across various platforms: