AUTOMATIC CLASSIFICATION AND PREDICTION USING TEXT DISPATCH DATA

PURDUE UNIVERSITY | The Data Mine

Fanyang Chang, Anay Gandhi, Maham Godil, Kushagra Govil, Isha Mahadalkar, Nikhil Mehra, Jay Palamand

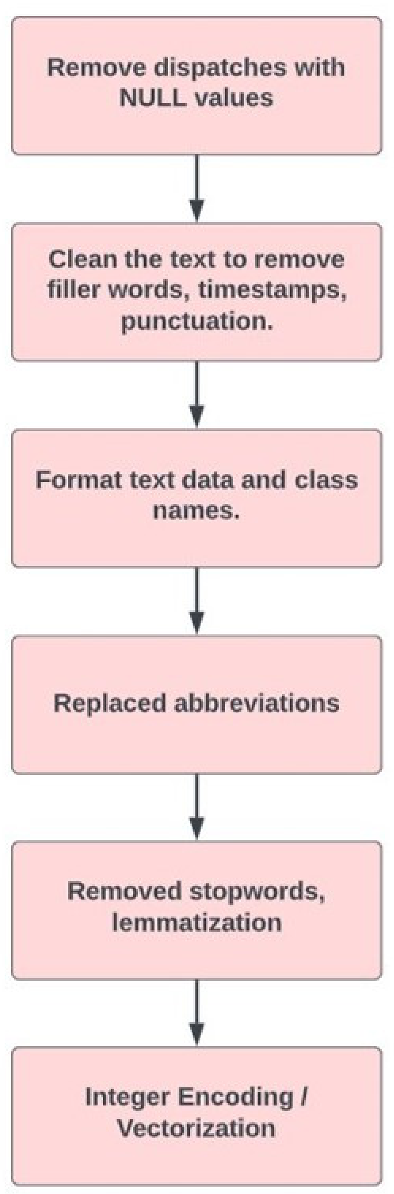
TESLA

INTRODUCTION

Motivation: Use existing data to develop tools/models that add value to Tesla generating leads that help Tesla enhance factory operations.

Goal: Given historical text and reliability data our goal is to create a model to automate the process of classifying open text maintenance records into standardized groupings. We also aim to predict future downtime and identify poor-performing equipment.

DATA PREPROCESSING & EXPLORATION



NaN removal, cleaning, formatting, stopword removal, vectorization.

[X, 2021-10-12 19:24:14.97] Observation: A, [Y, 2021-10-12 19:38:54.933] Observation: Text., [Y, 2021-10-12 19:39:00.353] Action Taken: Text

'failure.mechanical': 0, 'failure.material': 1, ... '

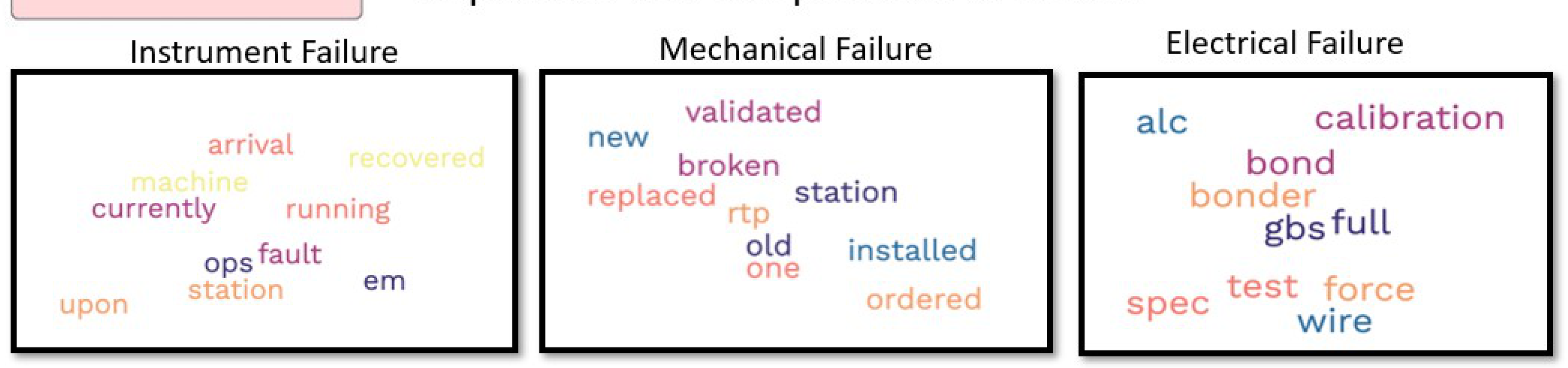
RTP – Return to Production, PM – Preventative Measures, HMI – Human Machine Intervention

Removed words like "*a, an, the, and, it, for, or, but, ...* "

Integer Encodings:
Text – [61, 73, 87, 102, 201, 194, 81, 150, 18, 124, 287, 3, 24, 48, 206, 2, 321, 0, 0, 0, 0]
Sparse Vectorization:
Text – [0,0,1,0,0,1,0,0.........,1,0,0,1,0......]

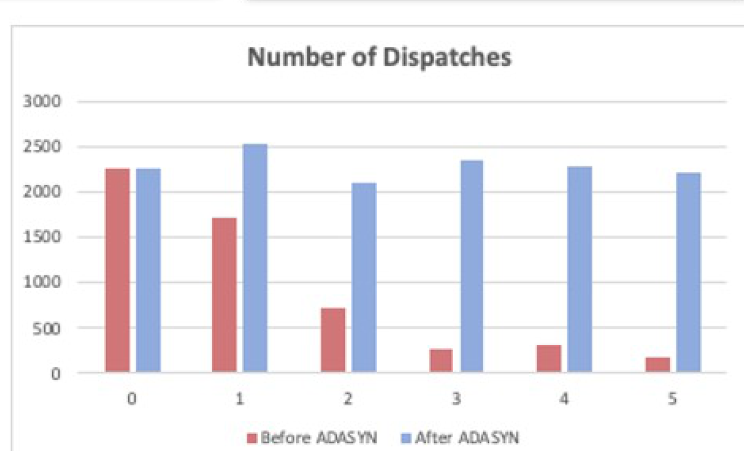
Clustering

We used distance-based KMeans clustering to analyze the dispatches and see patterns in words.



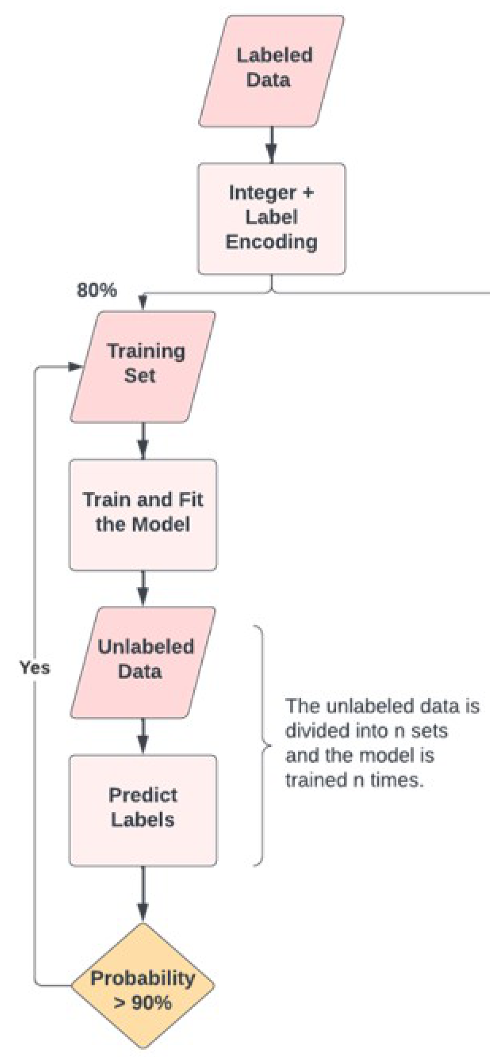
ADASYN

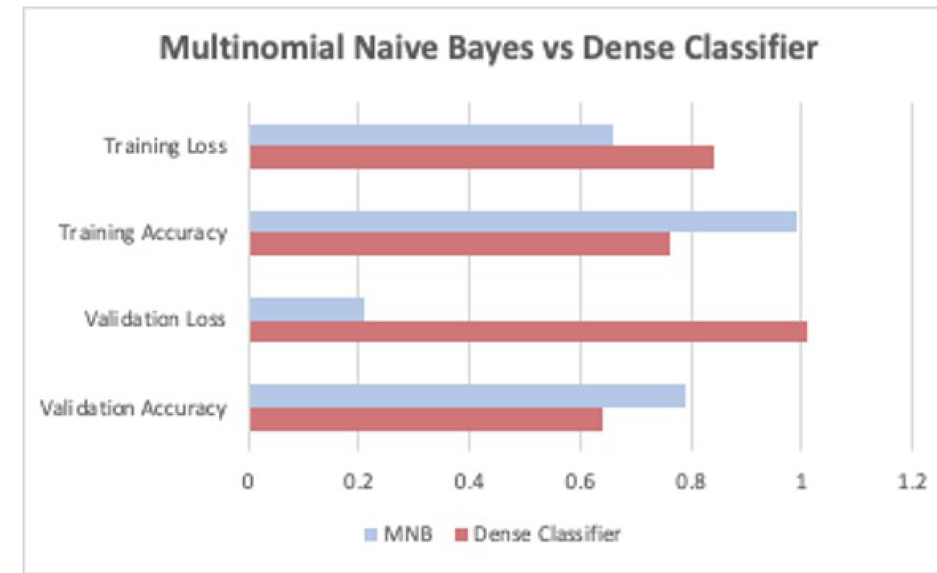
ADASYN was applied to handle class imbalance and generate synthetic vectors for the minority classes using weighted distribution. These vectors balance the dataset, resulting in improved performance for the classification of the minority classes.



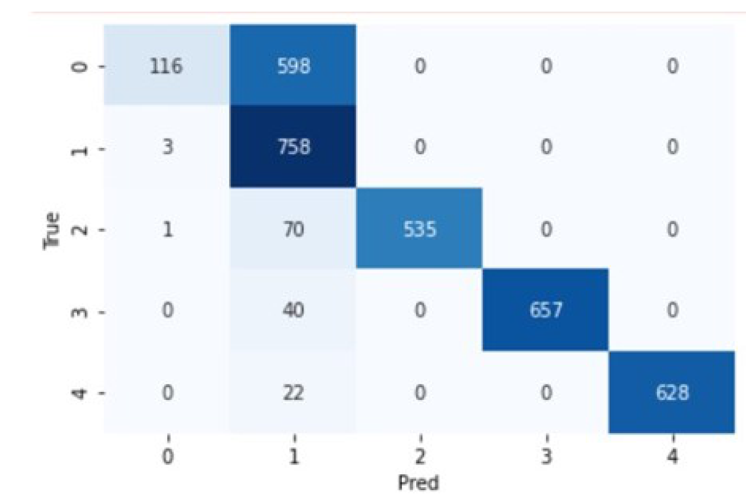
NATURAL LANGUAGE PROCESSING

We trained, evaluated, and compared models using **Dense Neural Network and Multinomial Naïve Bayes** to classify the dispatch data with high accuracy using the semi-supervised approach.



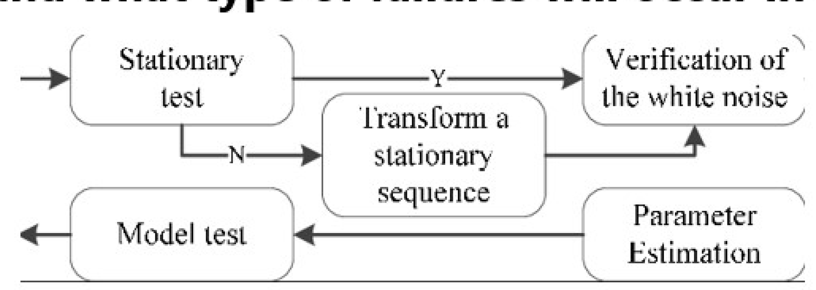


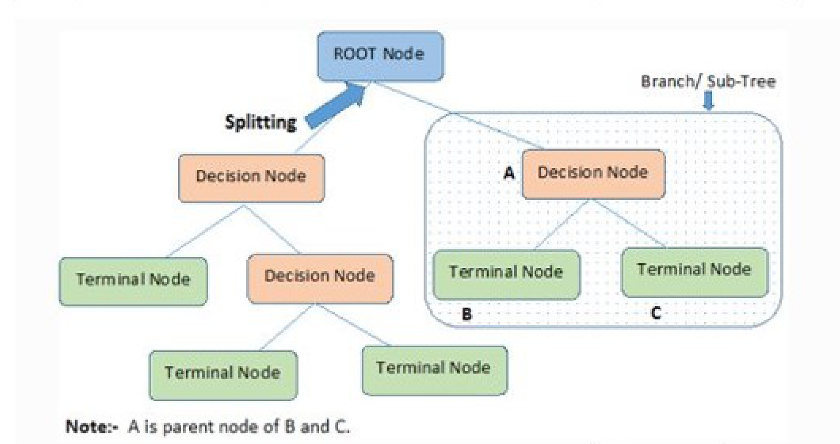
Confusion Matrix: Diagonal elements correspond to correctly predicted cases):

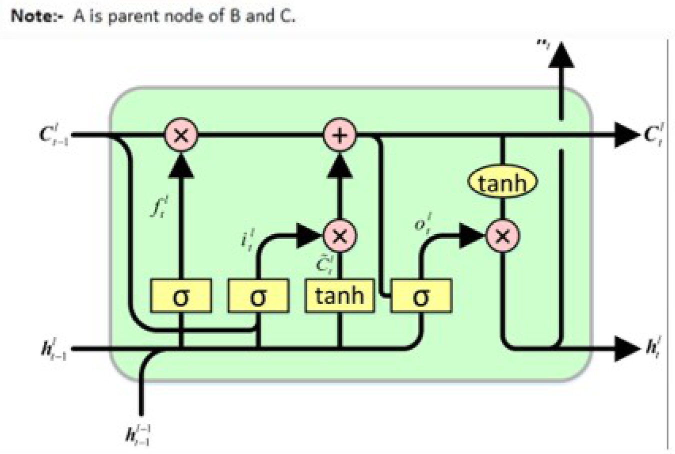


PREDICTION METHODS

Detect anomalies within the battery production data and predict when and what type of failures will occur in each hour.







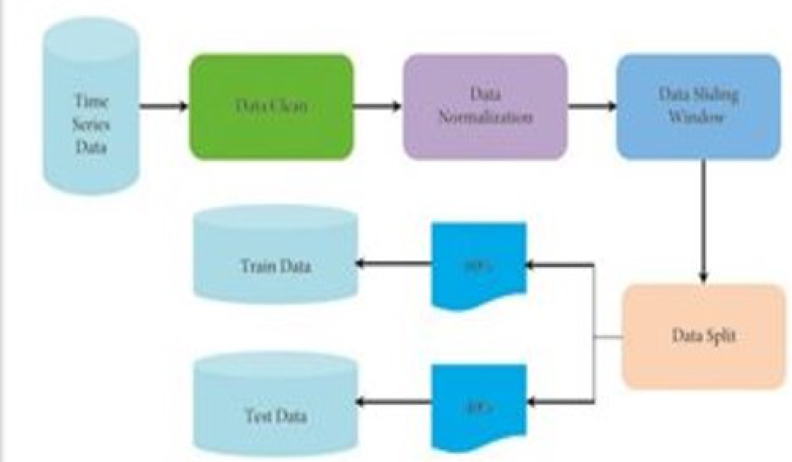
Methods: We separated trend, seasonality, and residual components of the time-series data through seasonal/trend decomposition.

Anomaly Detection: Use binary detection to flag a trend as an anomaly and send an alert.

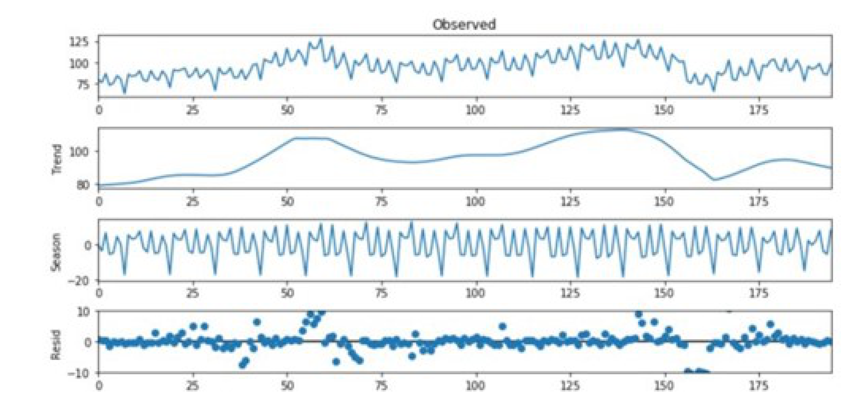
Time-Series Forecasting: By training ARIMA, we forecast the number of items produced per line for the next X hours and send an alert if these values are below a certain threshold.

LSTM Prediction: Training a LSTM RNN to predict the number of future failures on each machine providing an estimated time of failure.

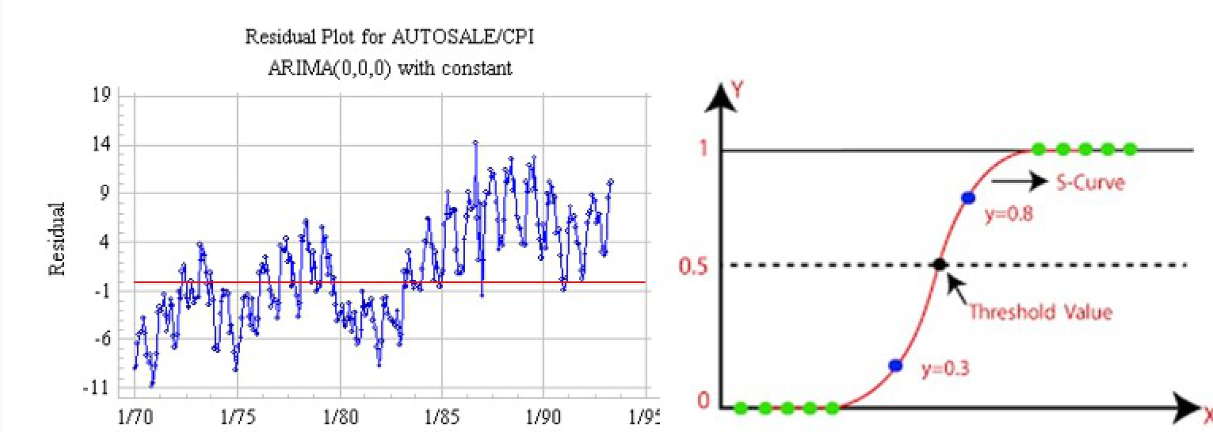
PREDICTION PROCESS & RESULTS



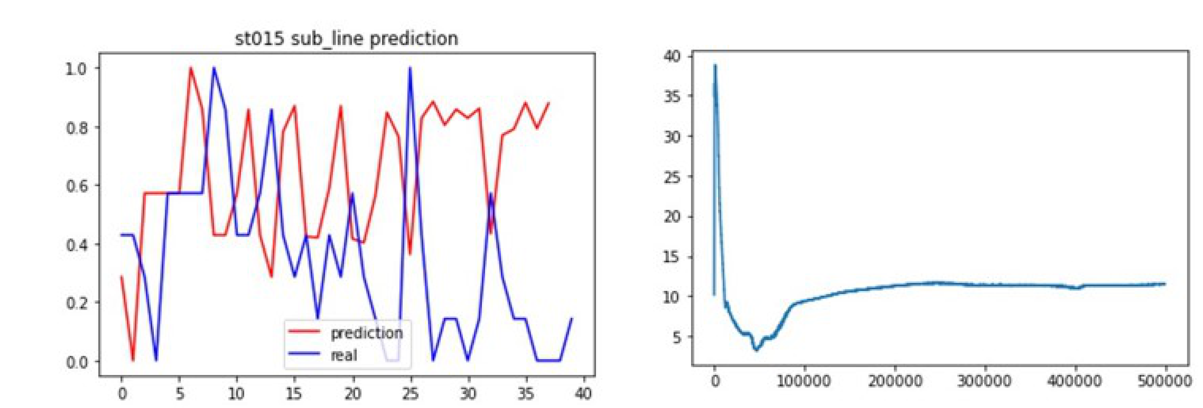
Data cleaning process:
1.Delete the missing values 2.Normalize data 3.Parse time stamp
Detrend the data: Used regression and smoothing to remove the cyclical component. **Feature engineering:** We implemented a rolling average and moving standard deviation.



Time-series forecasting:
The trend line represents the residual plot for the Autosale ARIMA
Input: timestamps, num of items produced per hour.
Output: predicted num of items next hour



Binary Classification: To determine the threshold for failure of a production line. **Stacked Random Forest, Logistic Regression:** To train model



LSTM: 15-day period, summation of prediction error equals to 2 when training through an epoch of 50000.

FUTURE WORK

NLP: 1. Fine tune the models by changing and testing with different hyperparameters and sampling techniques. **2.** Update the models so that it classifies the dispatches into sub-categories for each failure group.
Prediction: 1. Update the logic for pretraining process of input data of LSTM model to the machine level. **2.** Incorporate the results from the NLP analysis, refine the provided failure data and update the prediction model increasing granularity down to the part/component level.

ACKNOWLEDGEMENTS

Our utmost gratitude to Tesla for their collaboration with the Data Mine. Thank you to our mentors Casey Justus, Allor Okoye, Doug Pillars, and Victor Reynosa for their continued support.
Thank you to the Data Mine and the accompanying staff.