**Real time monitoring for wire-EDM process using Machine Learning (KI-Erosion)** [**[link]**](https://1drv.ms/b/s!AqlHBV7Y0ExBgshvSgtk662qgDMTfQ?e=wf8Ko1)

**Objective**: Improve precision in Wire Electrical Discharge Machining (EDM) through real-time quality monitoring using machine learning.

**Problem Addressed**: Traditional Wire EDM processes lack real-time feedback, leading to inconsistencies in machining quality which are only realized after the measurements with CMMs.

**Solution approach:**

* Use of sensor data to capture various machining and process parameters (e.g., voltage, current, wire speed).
* Preprocessing of the current voltage into features with process knowledge
* Application of machine learning algorithms to correlate geometrics curvature error to quantize the **quality of the cut part (QA)**

**ML techniques / Framework:**

* Supervised learning, ensemble regression model
* SHAP for model interpretation

**Potential Applications**: Industrial manufacturing, aerospace, and automotive industries where high-precision machining is critical. The use-case in this project was milling for Fir-Tree slots.

**Automated pre-processing approach for ML analysis of tabular dataset** [**[link]**](https://www.thinkmind.org/library/COLLA/COLLA_2022/colla_2022_1_10_50012.html)

**Objective**: Automated approach to preprocess tabular dataset that includes feature creation as well as sampling approach

**Problem addressed**: lack of major advancements in data preprocessing for tabular datasets in the field of Machine Learning (ML). Explores feature engineering, feature selection, target discretization, and sampling in an automated fashion.

**Solution approach:**

The project proposes an automated preprocessing pipeline that integrates feature selection, feature engineering, target discretization, and a novel Bin-Based sampling method to improve ML model performance on tabular datasets. The pipeline is validated using RandomForest and AutoML libraries, showing significant improvements for baseline models and marginal enhancements for AutoML.

**ML techniques / Framework:**

* RandomForest, Autogluon, Autosklearn, H2O
* Stratified sampling, KL-divergence,

**Potential Applications**: Useful tool to preprocess dataset to use in conjunction with AutoML libraries. Useful to create new features for manufacturing dataset, ex. Automated generation of EnergyInput can be calculated with current, resistance and welding time.

**Non-destructive testing for Resistance Spot Welding by AI based Ultrasonic testing [**[**link**](https://www.researchgate.net/publication/385648388_Deep_Learning_for_Weld_Measurement_Extraction_via_Ultrasonic_Monitoring_of_the_Resistance_Spot_Welding_Process)**]**

**Objective**: This work develops AI-driven semantic segmentation for ultrasonic data interpretation in RSW monitoring, enabling automated feedback control, improving NDE methodologies, and enhancing manufacturing efficiency and vehicle safety.

**Problem addressed:**

Traditional open-loop resistance spot welding (RSW) control is becoming less effective due to the adoption of next-generation materials and dissimilar material joints, yet statistical destructive and nondestructive tests (NDE) remain the primary evaluation methods, limiting automation and efficiency.

**Solution Approach:**

* Develops AI-driven semantic segmentation techniques to interpret ultrasonic data for post-process and in-process monitoring of resistance spot welding (RSW).
* Uses segmentation mask data to estimate weld measurements by leveraging prior knowledge about the welding process.

**ML techniques / Framework:**

* U-Net architecture, Vision transformers, Active learning
* Tensorflow, SuperAnnotate

**Potential Applications**: Ultrasonic data interpretation and automated weld evaluation can be applied in automotive manufacturing, aerospace, and industrial welding for real-time process monitoring, quality control, and smart manufacturing (NDE 4.0)

**Reinforcement learning for optimizing manufacturing process parameters to reduce scrap** [**[link]**](https://ebooks.iospress.nl/doi/10.3233/ATDE230059)

**Objective:** Develop a reinforcement learning (RL) framework for real-time process parameter optimization to enhance quality, reduce scrap, and improve efficiency in manufacturing.

**Problem addressed**: Traditional **optimization algorithms** (e.g., PSO, GA) are computationally expensive and unsuitable for real-time **process control**, while predictive models reduce inspection costs but do not actively improve quality.

**Solution Approach:**

* Use Hybrid-MPO RL to optimize numerical and categorical process parameters.
* Trains a predictive quality model (PQ-model) as a surrogate for real-time optimization.
* Compare RL-based optimization with PSO, GA, SA, DE, BH, showing superior speed and efficiency.

**ML techniques / Framework:**

* Reinforcement Learning (RL): Hybrid-MPO, DQN, DDPG.
* Baseline Algorithms: GA, PSO, SA, DE, BH

**Potential Applications:** The proposed RL framework enhances manufacturing process optimization in metal forming, welding, and 3D printing by enabling real-time adaptive control to reduce defects. It supports smart manufacturing by aiming to zero-waste production which can enhance field like automative, aerospace, semiconductor industries.

**ARES: Automated machine learning framework for structured and time series data [**[**video link**](https://www.youtube.com/watch?v=eOhOm_Xxt3k&t=34s&ab_channel=IconPro)**,** [**poster link**](https://iconpro.com/wp-content/uploads/2023/05/ARES-User-Stories_ENG_Mar2023.pdf)**]**

**Objective:** IconPro ARES is designed to streamline the machine learning lifecycle, from data preparation to model deployment, enabling efficient experimentation, model validation, and real-world application in predictive analytics and process optimization.

**Problem Addressed**: Traditional machine learning workflows require manual data handling, model training, and deployment, leading to inefficiencies and inconsistencies. Additionally, ensuring reliable predictions, detecting out-of-distribution (OOD) data, and optimizing process parameters remain challenging in dynamic industrial environments.

**Solution Approach:**

* Automated ML pipeline integrating data preparation, model training, validation, and deployment for tabular and timeseries datasets
* Out-of-Distribution detection to ensure prediction reliability by flagging unfamiliar data.
* Feature Importance analysis using SHAP for interpretable model insights.

**ML Techniques / Framework:**

* Supervised Learning: Predictive models for classification and regression.
* Out-of-Distribution (OOD) Detection: Identifies data drift to enhance model reliability.
* Feature Importance (SHAP Analysis): Quantifies feature impact on predictions.
* Optimization Algorithms: Process parameter tuning using predictive models.

**Potential Applications:** ARES can be applied in smart manufacturing, quality control, and industrial automation for predictive maintenance, defect detection, and process optimization. Industries such as automotive, aerospace, and semiconductor manufacturing benefit from AI-driven decision-making, ensuring improved efficiency, reduced waste, and adaptive real-time process control.

**SaaS Software development with Kubernetes based microservices (AutoML) [**[**link**](https://iconpro.com/wp-content/uploads/2023/05/ARES-User-Stories_ENG_Mar2023.pdf)**]**

**Objective**: The objective of this software development project is to build a scalable, resilient, and efficient Software-as-a-Service (SaaS) AutoML platform that enables users to automate the end-to-end machine learning pipeline. By leveraging Kubernetes-based microservices, the system ensures high availability, fault tolerance, and seamless deployment of machine learning models at scale. Scaling an MVP for a startup is a challenging task especially due to low budget and minimum time to market. Achieving this requires strategic planning and execution. I happened to lead the teams for development and meanwhile also learned the necessary tech stack and development guidelines.

**Tech stack**:

* RabbitMQ: communication between microservices with subscribe and publishing method
* Redis: For in-memory
* Spark: For distributed computing for feature extraction and data preparation inside Kubernetes clusters
* OpenAPI 3.1: for defining HTTP interfaces
* Database worked on: S3, PostgreSQL
* Apache Drill: connecting different databases
* Gloo Edge: for smart routing request from outside to the appropriate service
* MLFlow: For storing, loading and deploying ML models.

**System Design:**

Helped designed software architecture for multi-tenant SaaS application with multiple microservices

Decided on the effectiveness of software architecture by choosing tech stack for effective communication

**Cloud operation:**

* Worked with Azure Cloud resources to create WebApp for
* Summary of task discussed with Praneeth the other day
* Discuss with Navid regarding ArgoCD and its usage

(a github link will be included here)

**Continuous Integration and deployment**:

* Discuss reg. CI and CD
* Learn about OpenShift cluster from Navid
* Learn about Edge devices

**Custom project**: Github MNIST Kubernetes

**Neural Networks for estimating process capability of manufacturing processes (Worked with Q-DAS team at Weinheim]**

**Objective:**

* Create a neural network based fast prediction model for identifying process capability index for Statistical Process Control software.
* Ship a C++ .dll for client to integrate in their software that led to enhance the speed 10x.

**Problem addressed:**

* Process control is very important in production to know the waste identification.
* Fast identification of Cp, Cpk value for process

**Solution Approach:**

* Data generation with statistical laws and variations
* Trained autoencoder based feature reduction from cumulative distribution function (CDF) using 1D-CNNs
* 10-classes extensive evaluation on real process data for validation

**Framework:**

Tensorflow, Pytorch, Python, C++