Industrial Internship Report on

"Quality Prediction of Mining Process"

Prepared by

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Executive Summary
This report provides details of the Industrial Internship provided by upskill Campus and The IoT Academy in collaboration with Industrial Partner UniConverge Technologies Pvt Ltd (UCT). This internship was focused on a project/problem statement provided by UCT. We had to finish the project including the report in 6 weeks' time. My project was Quality Prediction of Mining Process This internship gave me a very good opportunity to get exposure to Industrial problems and design/implement solution for that. It was an overall great experience to have this internship.

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1 Preface

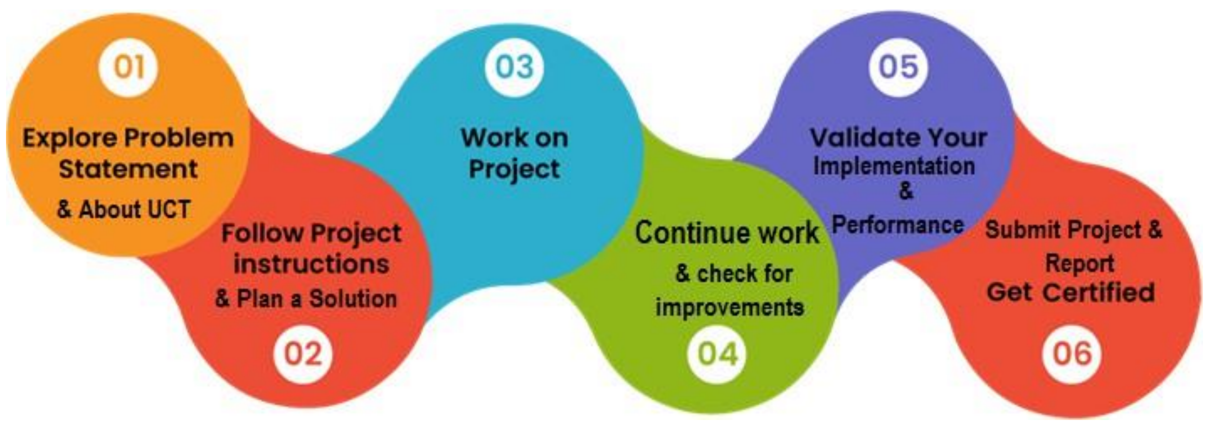
Summary of the whole 6 weeks' work.

About need of relevant Internship in career development.

Brief about My project/problem statement.

Opportunity given by USC/UCT.

How Program was planned



Your Learnings and overall experience.

Thank to all (with names), who have helped you directly or indirectly.

Your message to your juniors and peers.

2 Introduction

2.1 About UniConverge Technologies Pvt Ltd

A company established in 2013 and working in Digital Transformation domain and providing Industrial solutions with prime focus on sustainability and RoI.

For developing its products and solutions it is leveraging various **Cutting Edge Technologies e.g. Internet of Things (IoT), Cyber Security, Cloud computing (AWS, Azure), Machine Learning, Communication Technologies (4G/5G/LoRaWAN), Java Full Stack, Python, Front end** etc.

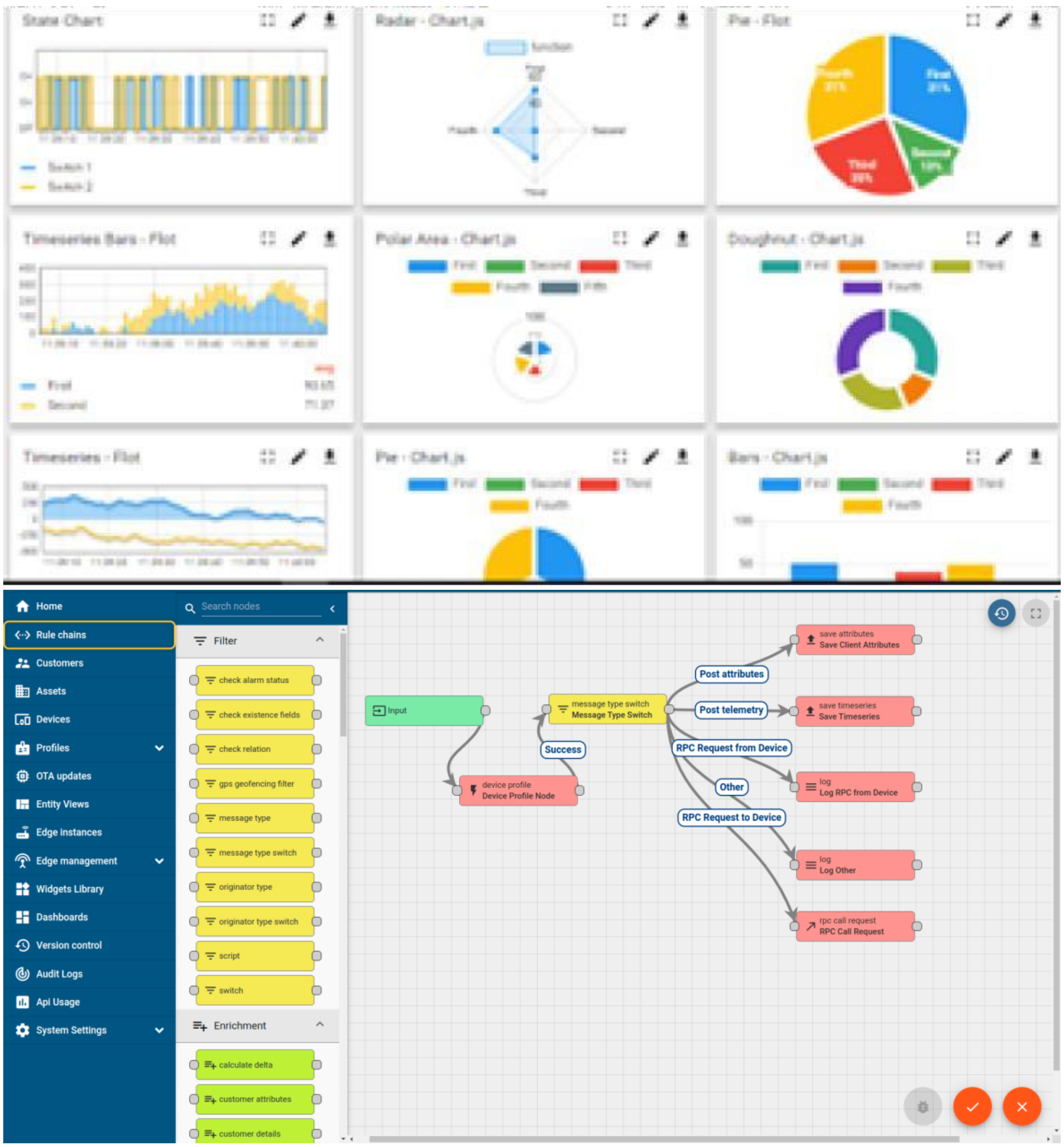
i. UCT IoT Platform (uct Insight)

UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable “insight” for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSQL Databases.

- It enables device connectivity via industry standard IoT protocols - MQTT, CoAP, HTTP, Modbus TCP, OPC UA
- It supports both cloud and on-premises deployments.

It has features to

- Build Your own dashboard
- Analytics and Reporting
- Alert and Notification
- Integration with third party application (Power BI, SAP, ERP)
- Rule Engine



ii. Smart Factory Platform (FACTORY WATCH)

Factory watch is a platform for smart factory needs.

It provides Users/ Factory

- with a scalable solution for their Production and asset monitoring
- OEE and predictive maintenance solution scaling up to digital twin for your assets.
- to unleased the true potential of the data that their machines are generating and helps to identify the KPIs and also improve them.
- A modular architecture that allows users to choose the service that they what to start and then can scale to more complex solutions as per their demands.

Its unique SaaS model helps users to save time, cost and money.

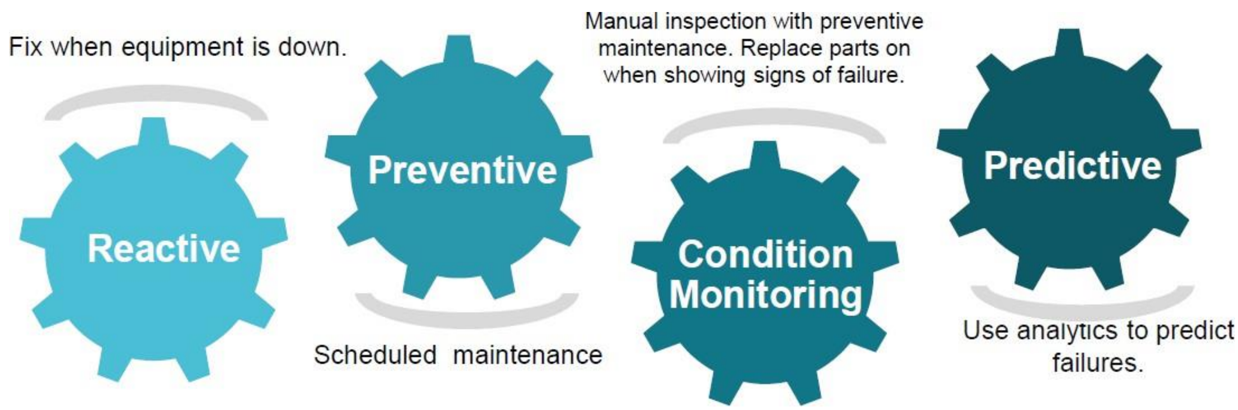
Machine	Operator	Work Order ID	Job ID	Job Performance	Job Progress		Output		Rejection	Time (mins)				Job Status	End Customer
					Start Time	End Time	Planned	Actual		Setup	Pred	Downtime	Idle		
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i

iii. LoRaWAN based Solution

UCT is one of the early adopters of LoRAWAN Technology and providing solution in Agri Tech, Smart cities, Industrial Monitoring, Smart Street Light, Smart Water/ Gas/ Electricity metering solutions etc.

iv. Predictive Maintenance

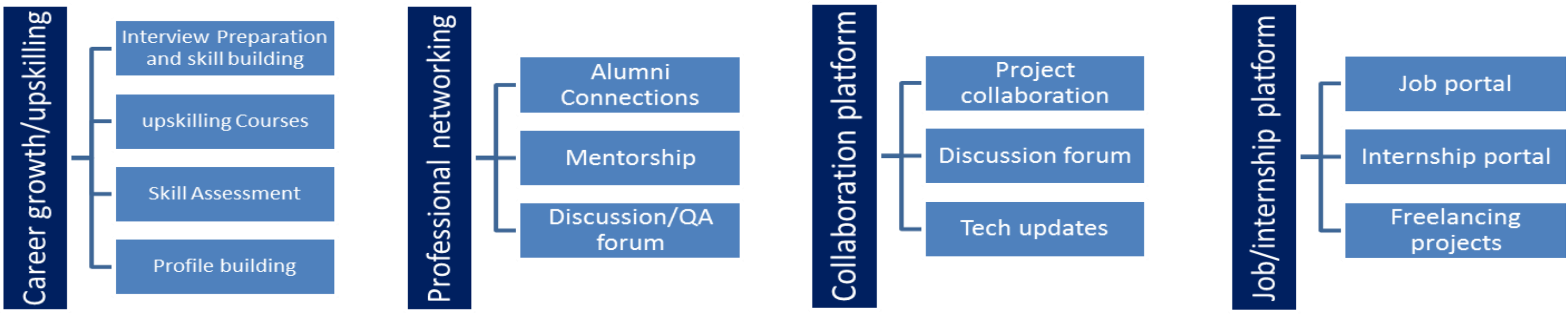
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



2.2 About upskill Campus (USC)

upskill Campus along with The IoT Academy and in association with Uniconverge technologies has facilitated the smooth execution of the complete internship process.

USC is a career development platform that delivers **personalized executive coaching** in a more affordable, scalable and measurable way.



2.3 The IoT Academy

The IoT academy is EdTech Division of UCT that is running long executive certification programs in collaboration with EICT Academy, IITK, IITR and IITG in multiple domains.

2.4 Objectives of this Internship program

The objective for this internship program was to

☛ get practical experience of working in the industry.

☛ to solve real world problems.

☛ to have improved job prospects.

☛ to have Improved understanding of our field and its applications.

☛ to have Personal growth like better communication and problem solving.

3 Problem Statement

Quality Prediction in Mining Process

In practice, management, metallurgists, and control operators rely on laboratory tests to make ad-hoc decisions for optimizing ore recovery quality in the froth flotation system. However, the lab analysis for determining iron ore and silica concentrate percentages takes over two hours, making it ineffective for real-time monitoring and control. This delay, combined with fluctuating ore feed and output requirements, complicates maintaining a steady state in the plant, affecting ore feed rates and reagent or air flow adjustments. Despite various studies, real-time estimation of silica concentrate remains challenging, particularly when it ends up in the tailings, leading to significant financial losses due to quality ore recovery being wasted. Therefore, there is a need for models that can efficiently predict and incorporate the stochastic nature of a flotation plant, providing a reliable platform for real-time decision-making.

4 Existing and Proposed solution

In the mining process, existing models like linear regression and random forest are used to predict ore quality. Linear regression offers simplicity and interpretability but may lack accuracy for complex patterns. Random forest improves prediction through ensemble learning but can still struggle with temporal dependencies. The proposed solution is Long Short-Term Memory (LSTM) networks, a type of recurrent neural network (RNN) designed to handle time-series data effectively. LSTMs capture long-term dependencies and intricate temporal patterns, providing more accurate and robust predictions for ore quality by leveraging sequential data and addressing the limitations of traditional models.

3.1 Code submission: -

(https://github.com/aniketkatkar20/upskillcampus/blob/main/QualityPredictionOfMiningProcess.ipynb)

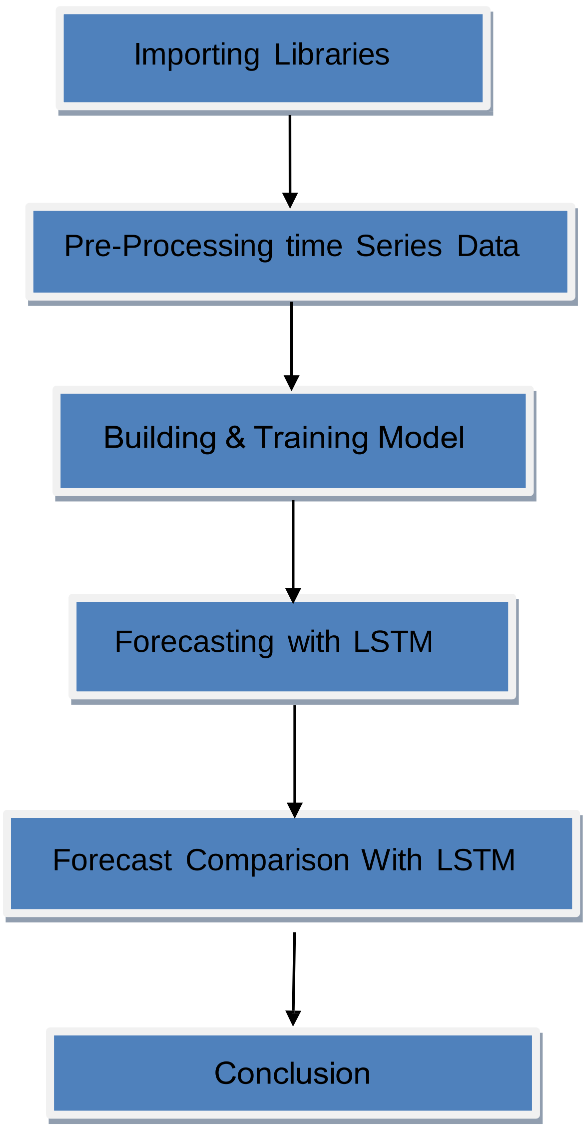
3.2 Report & Others: -

(https://github.com/aniketkatkar20/upskillcampus)

5 Proposed Design/ Model

The proposed LSTM model for predicting ore quality in a mining process involves several steps. First, preprocess historical mining data to create a time-series dataset, normalizing features and splitting it into training and testing sets. Construct an LSTM network with multiple layers, each comprising LSTM units to capture temporal dependencies. Add dropout layers to prevent overfitting. Train the model using the training dataset, optimizing with backpropagation through time. Validate and test the model using unseen data, fine-tuning hyperparameters for improved accuracy. Finally, deploy the model to provide real-time quality predictions, facilitating enhanced decision-making and operational efficiency.

Flow Chart


Importing Libraries
Pre-Processing time Series Data
Building & Training Model
Forecasting with LSTM
Forecast Comparison With LSTM
Conclusion

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6 Performance Outcome

The forecast evaluation results show that the LSTM model outperforms the Random Forest model in terms of both mean absolute error (MAE) and root mean squared error (RMSE). The LSTM model achieves a lower MAE of 0.4791 compared to 0.5875 for the Random Forest model, indicating that, on average, the LSTM's predictions are closer to the actual values. Similarly, the LSTM model demonstrates a lower RMSE of 0.7021 compared to 0.7679 for the Random Forest model, suggesting that the LSTM's predictions have smaller deviations from the observed values.

The superior performance of the LSTM model can be attributed to its ability to capture temporal dependencies and intricate patterns in the time-series data, which are crucial in forecasting the quality of the mining process. Unlike Random Forest, which builds multiple decision trees independently and combines their outputs, LSTM incorporates feedback connections that enable it to retain information over long sequences, making it better suited for modeling sequential data.

These evaluation metrics underscore the effectiveness of LSTM in this specific mining context. The lower MAE and RMSE values indicate that the LSTM model provides more accurate predictions of ore quality, which can lead to improved decision-making in the mining process. By leveraging LSTM's capabilities, mining operations can optimize resource utilization, enhance productivity, and ultimately increase profitability by making informed decisions based on more accurate forecasts. Therefore, the LSTM model emerges as a promising solution for quality prediction in mining processes, offering superior performance compared to traditional approaches like Random Forest.

7 My Learnings

- Choosing the right model, such as LSTM for time-series data, can significantly enhance prediction accuracy by effectively capturing temporal dependencies.

- Using metrics like MAE and RMSE is crucial for assessing model performance and comparing different models to determine the best fit.

- Proper data cleaning and normalization are essential steps to ensure high-quality input data for accurate and reliable predictions.

- Advanced models like LSTM can handle complex patterns in data better than traditional models, improving prediction accuracy.

- Temporal Dependencies: Recognizing and leveraging temporal dependencies in data is key to improving predictions in time-series analysis.

- Understanding the limitations of traditional models, such as linear regression and random forest, helps in selecting more suitable advanced models for specific tasks.

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8 Future work scope

- Combine LSTM with other models for enhanced prediction accuracy through ensemble learning techniques.

- Explore additional input features to capture more nuanced relationships and improve model performance.

- Optimize LSTM parameters to fine-tune model performance and increase predictive power.

- Expand dataset through techniques like synthetic data generation to improve model robustness and generalization.

- Develop mechanisms for continuous model updating to adapt to evolving mining process dynamics.

- Incorporate methods to quantify prediction uncertainty, enhancing decision-making and risk management in the mining process.