Energy Networks Innovation Process

Project Closedown Report Document

Date of Submission: 06/06/2024

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Project Title (*This cannot be changed once registered*)	Project Reference
Storm AI	NIA_SSEN_0065
Funding Licensee(s)	**Project Start Date**
Scottish Hydro Electric Power Distribution	December 2022
Project Duration	**Year**
16 months	2024
Nominated Project Contact(s)	
Tim Sammon, Innovation Programme Delivery Manager at SSEN	

1. Scope

The Storm AI project is a demonstration project that will test if Artificial Intelligence (AI) or Machine Learning (ML) can be employed to increase the amount of actionable data provided to SSEN via a customer report on Power Track. The main benefits to customers will be in relation to increase accuracy in the Estimated Time of Restoration (ETR). Benefits to Distribution Network Operators (DNO) will be due to greater efficiency during storms and weather events this is estimated at £2,061k for the next five years based on assumed similar weather patterns. The broadly proposed scope of works for the Storm AI project will cover.

• Research into the proposed use of AI and ML in Power Track and possible solutions
• An understanding of additional data sets available in SSEN that could provide useful contextual data for Power Track
• Subject Matter Experts from SSEN feeding the AI and ML algorithms
• Field trial of AI and ML solution
• Stakeholder engagement and feedback on the solution to ensure its appropriateness

2. Objective(s)

The objectives for the project are as follows.

• Understand how AI and ML can improve SSENs response in a storm
• Develop power track using AI and ML to leverage additional value from the data submitted to SSEN from customer reports in Power Track
• Understand how AI and ML can be utilised to improve the response to customers and the accuracy of ETRs provided

3. Success Criteria

The project will be deemed as successful if all items in the scope, objectives and learnings are achieved and this will contribute to advancing industry response to customer in storm conditions.

4. Performance compared to the original project aims, objectives and success criteria

Details of how the Project is investigating/solving the issue described in the NIA Project Registration Pro-forma. Details of how the Project is performing/performed relative to its aims, objectives and success criteria.

The project looked into the use of machine learning techniques – notably those generally grouped under the umbrella of computer vision – to classify images submitted by customers of storm damaged assets. Two main avenues of classification were considered; paid-for machine-learning-as-a-service (MLaaS) solutions, such as Google's Vertex AI and Amazon's AWS Rekognition, and an in-house solution constructed within the Python programming language. The use of Microsoft's AzureML as a "half-way" between the two avenues was also considered, using an Azure virtual machine to run in-house written code however, this was discounted due to being more complicated to run and not offering a particularly easy-to-use interface.

Within the MLaaS solutions, Google's Vertex AI was discounted due to complexity in its use. The two options taken forward for further investigation were AWS Rekognition and an in-house construction. Ultimately, due to considerations of costs, customisability, and transparency in model functions, the in-house construction was selected to take forward.

The in-house option consists of a Python package constructed by Open Grid Systems, built within the PyTorch framework and training models based on the "Efficient B4" computer vision algorithm. Through the build of the Python package, various other methods were trialled, and the first iteration of the classifier used a custom-built, ten-layer Convolutional Neural Network (CNN) model.

The initial model was altered when the requirement to be able to predict multiple labels per-image under the Asset Type category was added. The new model set-up provided improved run-time and prediction accuracy over the initial ten-layer CNN.

Within the package, there are two main processes – model training and inference these are shown in Figure 1 as high-level process flows. For model training, the model takes in pre-processed image and label data, passed through a pre-processing module within the Python package, and trains over a number of epochs in an iterative fashion. Through each epoch, the model validates itself on a subset of the training data to reevaluate the weights and biases within the model parameters for the next epoch. At the end of training, the model is tested on a previously unseen subset of the data and is then saved. The saved models are then callable either for retraining or for inferences. A more in-depth view of the model training process is shown in Figure 2.

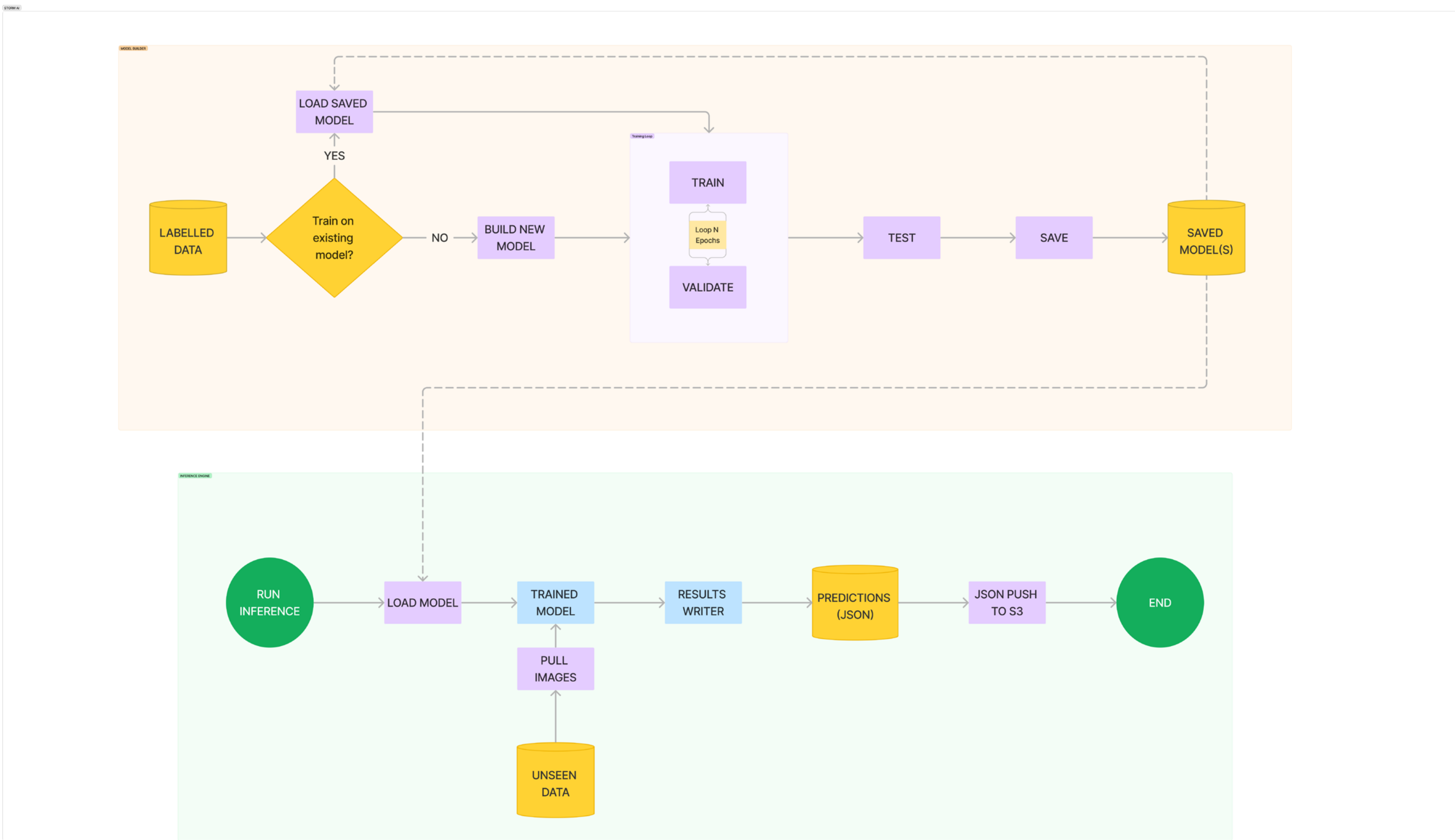

Figure 1 - High level overview of the model training (yellow) and inference (green) process flows

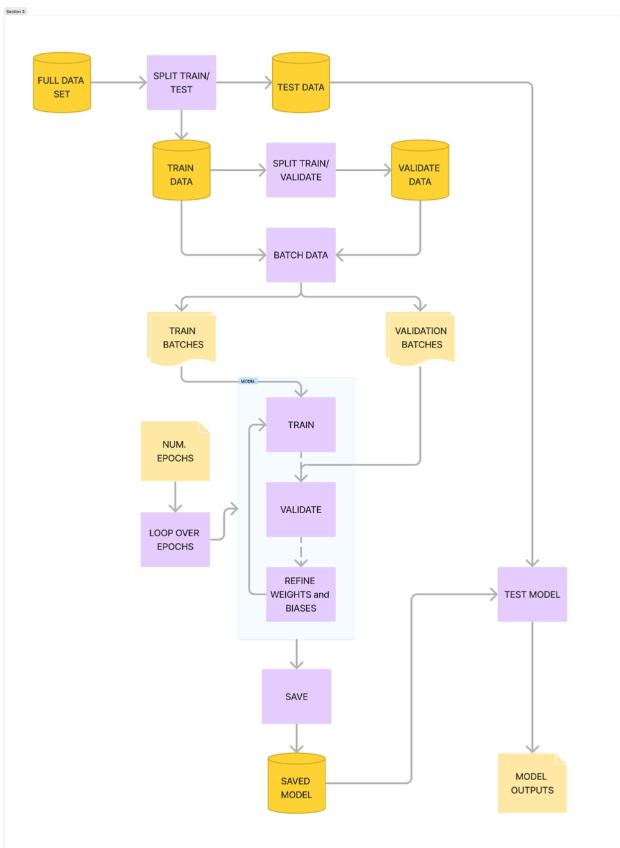

Figure 2 - Model training overview

The inference engine within the package is the main process that is built to be used by Power Track. Power Track being the main source of images with possible damages to our network. This process takes in a set of unseen images, loads in the various saved models and runs predictions using those models. The predictions are for asset type, voltage, risk to public, time to repair, tree cutting and traffic management required. The predictions are then saved as a JavaScript Object Notation (JSON) payload for being passed into the Concert back-end of Power Track for inspection by SSEN staff working on the fault desk.

For example, an image of a tree over a road that has pulled a pole and line down, we would expect the prediction to return, asset type pole and overhead line, severe risk to public, 6-12 hours to repair, voltage 11Kv, tree cutting required and traffic management required.

The initial performance of the model on the small set of labelled data available to the model shows promise, with all target sets being predicted with accuracy scores in excess of random chance. Notably, even the subjective “Risk Level” target is predicted with an accuracy of c.61%.

Work still needs to be done to refine the multi-label classification capabilities of the asset type prediction, however, it is expected that this will be made easier with increased access to labelled training data. This refinement work will be carried out as part of a gradual Business as Usual (BaU) roll-out of the solution into Power Track.

5. Required modifications to the planned approach during the course of the project

The Network Licensee should state any changes to its planned methodology and describe why the planned approach proved to be inappropriate. Please confirm if no changes were required

Initial project proposals and discussion looked into the use of AI and ML models for the prediction of various outage and damage characteristics that were eventually discounted, such as fault type, number of customers affected, and resources required to restore supply. For the time being, Storm AI has been limited to predicting asset damage information such as asset type, voltage level, risk level, estimated time to repair, and requirements for tree cutting and traffic management as part of the repair efforts.

The reasoning for this move is to limit the model's work to characterise that are likely to be obtainable purely from image data. Discounted elements would also require expert knowledge and data relating to the physical network model and customer/meter data. With future integration to Power Track and the supporting network and customer data, this may be achievable, however, this will require additional work.

Another advantage of limiting the initial functionality to the retained prediction targets is simplicity in training. A smaller number of targets to predict will allow for more targeted model training, and thus a more reliable model. The key retention is estimated time to repair, which may be used to provide consumers with more reliable estimates for time of power restoration.

6. Lessons learnt for future projects

Describe how the project (methodology, stakeholder engagement etc.) changed, or provided opportunities, from your expectation at the start of the project and therefore could be useful for a future project. In addition, please discuss the effectiveness of the research development or demonstration undertaken.

Efforts based around the improvement of the model's performance in prediction were hampered to some extent by a lack of available classified image data samples on which to train the model. Efforts were made to introduce dataset augmentation; however, these greatly increased computation time, code-base complexity, memory usage, and exacerbated existing dataset biases (i.e. an imbalance in samples of different data labels across the set) without substantial increases in model performance.

As such, the efficacy of the model to be deployed into Power Track was not quite where it could be with due to the limited set of training data. A larger set of training data would be highly beneficial. Fortunately, this issue has been planned for with the inclusion of the ability to save models and their respective states after training. This has the effect of allowing a trained model to be retrained on new data, without having to train on the full set every time, thus allowing the model to be updated as new data is labelled.

As a learning point, for any machine learning driven project going forward, there should be as much labelled data as possible to ensure reliable and useful results are delivered. It should be noted that allowing for the model to be continually retrained, new data can be fed in as it becomes available.

The inclusion of multi-label classification for the prediction of asset types, including the ability to identify multiple assets in one image, has provided was challenging. This is a more complex operation than identifying a single damaged asset within an image for the model and requires additional steps within the model's operations to train. Due to the complications in performing multi-label classification within the existing model, there are still issues to be worked through in regard to its predictive performance. This does not affect the overall functionality of the model and will not block its initial integration with Power Track but will require refining prior to being able to provide wholly reliable predictions.

7. The outcomes of the project

When available, comprehensive details of the Project's outcomes are to be reported. Where quantitative data is available to describe these outcomes it should be included in the report. Wherever possible, the performance improvement attributable to the Project should be described. If the TRL of the Method has changed as a result of the Project this should be reported. The Network Licensee should highlight any opportunities for future Projects to develop learning further.

Storm AI is planned to be integrated as a beta feature of SSEN's Power Track tool, a customer facing outage notification and reporting tool that allows consumers to see reported outages (along with planned/unplanned status, estimated time to restoration, and the status of the repair work), as well as reporting outages or damage to SSEN equipment. It's currently planned as a BETA product as we expand the training data to increase the accuracy of the predictions. This will result in a BaU deployment of Storm AI.

8. Data Access & Quality Details

A description of how any network or consumption data (anonymised where necessary) gathered in the course of the Project can be requested by interested parties. Please include a link to the publicly available data policy.

For information how to request data gathered in the course of this project, see Network Innovation Competition (NIC) and Network Innovation Allowance (NIA) Data Sharing Procedure at https://ssen-innovation.co.uk/innovation-strategy/.

9. Foreground IPR

A description of any foreground IPR that have been developed by the project and how this will be owned.

Not applicable

10. Planned implementation, recommendations or next steps

Please describe the next steps to implement this innovation project. What policies and standards need to be updated or created as part of this implementation.

Storm AI is planned to be integrated as a feature of SSEN's Power Track tool, a customer facing outage notification and reporting tool that allows consumers to see progress on ongoing outages. Storm AI will take photos submitted by customers as part of their reports and pass them through its inference engine. The results of this inference are then passed through to the *Cimphony Concert back-end, for engineers to view. A high-level architecture of the planned implementation is shown in Figure 3.

The Power Track front-end will be configured to deliver images to an Amazon S3 bucket, with the Storm AI inference engine monitoring the bucket at regular intervals for new images. The inference engine will then pass the JSON payloads containing predicted labels to a new S3 bucket being monitored by the Cimphony Concert back-end of Power Track, with the potential to configure notifications based on conditions (such as high predicted risk to life posed by a damaged asset).

The aims for implementation through Power Track are in three stages:

1. Initial integration as demonstration of BaU potential
2. Continued training of model on new data for damage triage assistance
3. Building towards triage automation continued training of the model could take the form of retraining the model a handful of times in the year, outside of storm seasons, on data labelled by SSEN engineers – this could be in the form of images classified initially by the inference engine and corrected as needed by engineers

The modular nature of the code allows it to be continually updated and adjusted as required to meet changing requirements as well as to cope with potential updates to open-source libraries used within.

*Cimphony Concert is a scalable, next generation Open Data Engine (ODE) for managing power system data. Cimphony Concert allows users to create a Digital Twin of their system, acting as a Network Model Management (NMM) system with full historical tracking of changes. The system supports the automatic integration of the as-built electrical network asset data with high-volume real-time data from smart meters, phasor measurement units, and Supervised Control and Data Acquisition (SCADA) measurement points.

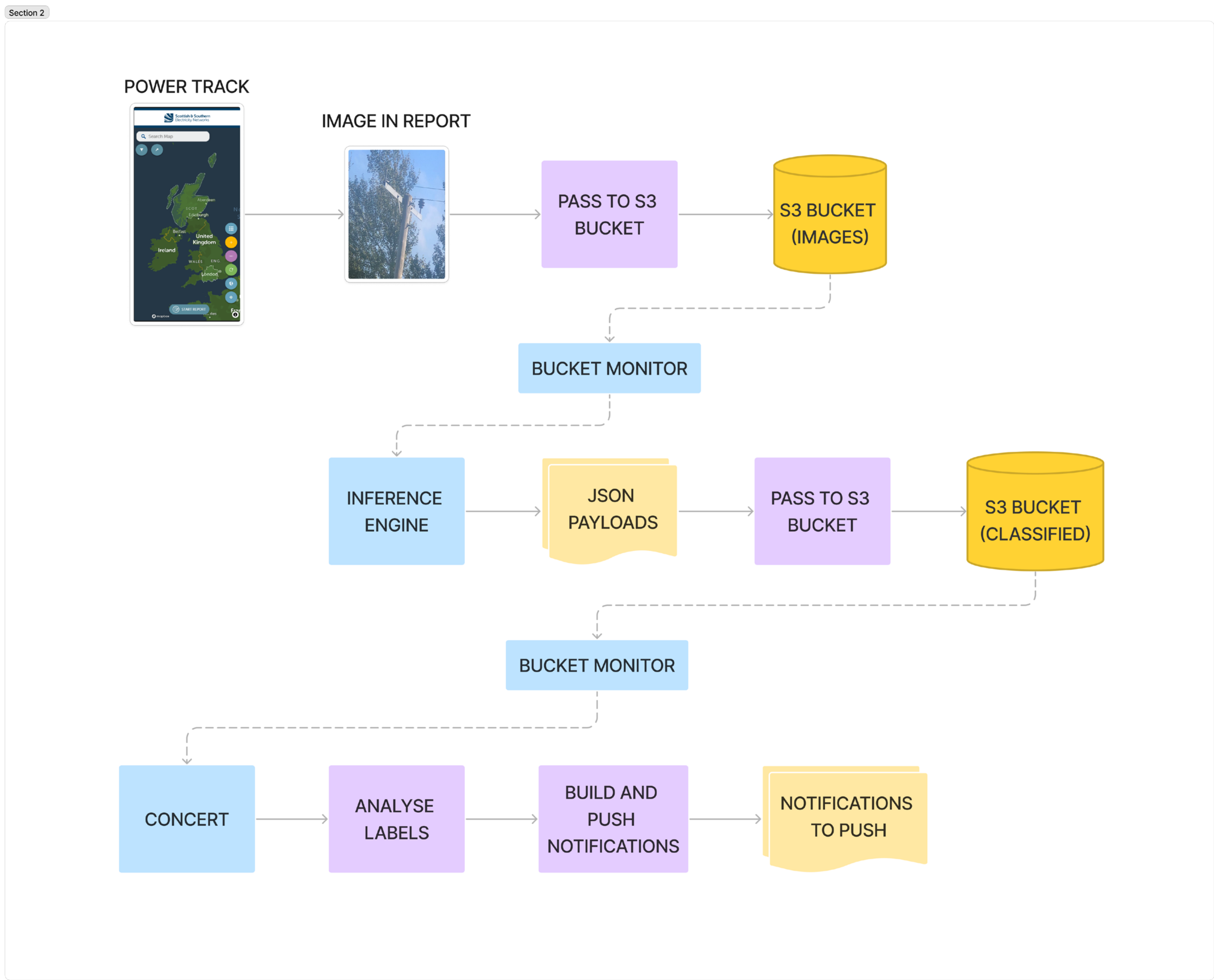

Figure 3 - Work flow integration from Power Track through to Cimphony Concert via Storm AI

Integration with Power Track is expected to allow for the processing of more images at a faster rate than is currently possible with fully manual labelling and triaging, thus freeing up SSEN staff and allowing engineers to be routed to site more quickly and more effectively. The integration with an existing solution, in the form of Power Track and the Concert back-end of Power Track, will allow for a swifter move to BaU, and the configurability of Storm AI's codebase and outputs, and Concert, will allow for notifications and outputs from Storm AI to the back end to be configured to meet SSEN's needs.

11. Other comments

12. Standards Documents

Identify any industry standards that may require updating due to the outcomes or understanding developed from this innovation project. If no standards will need to be updated, please state - not applicable

Not applicable