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Application of AI and ML to Distributed Detector Networks

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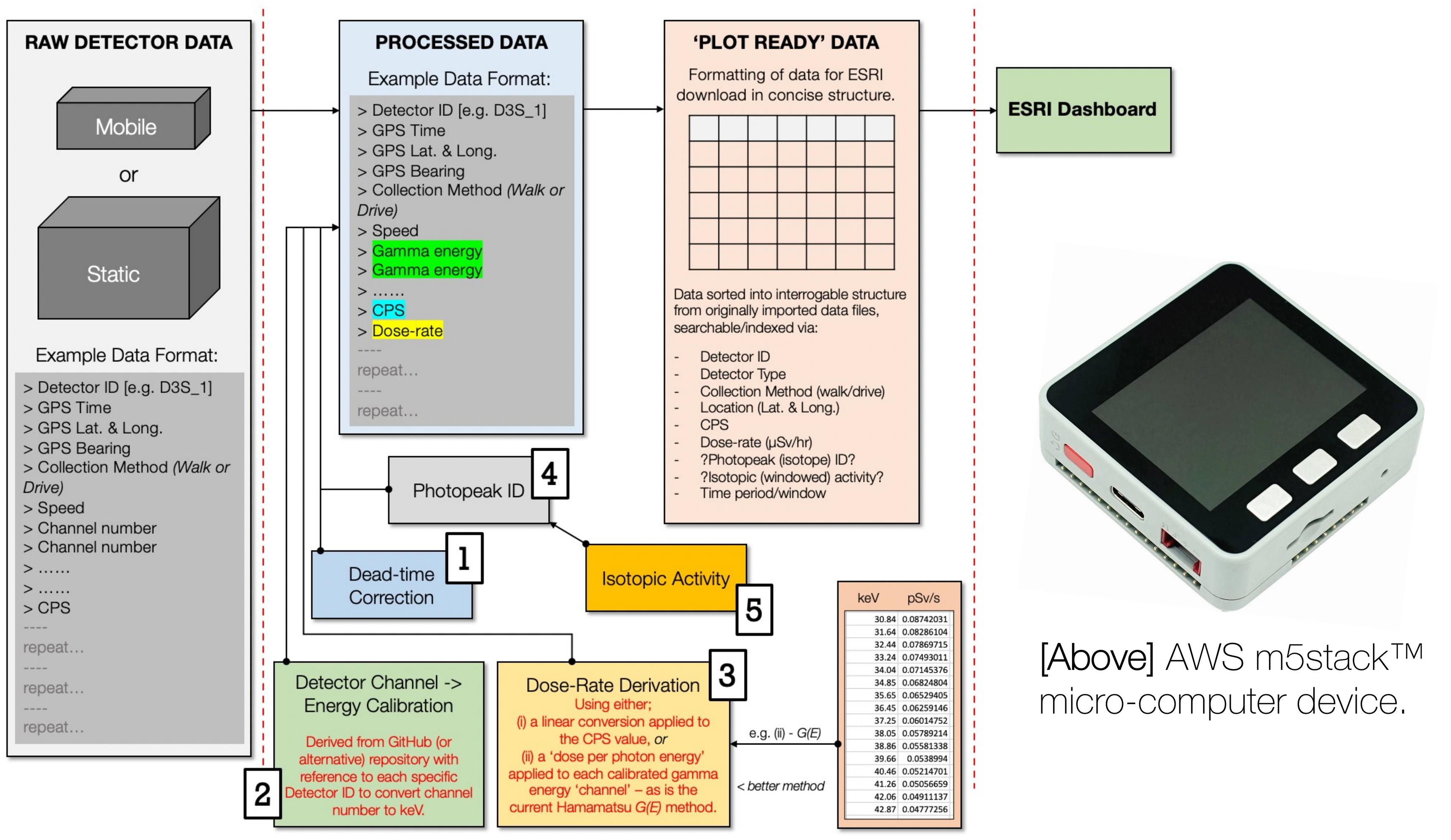
The progress in Machine Learning (ML) over the past decade has served to pioneer technologies such as self-driving (or 'driverless') cars or enhanced weather forecasting. However, such computational intelligence to analyse, interpret, and streamline the potentially vast radiological monitoring dataset that is/could be continually collected using multiple survey 'nodes' as part of the UK's national nuclear safety and security, has yet to be applied. Presently, individual detection events are each investigated as no wider "situational context" to the occurrence is applied – this is hence inefficient, costly and time-consuming as well as blind to small-scale/transient variations (and slow increased in activity) that may otherwise be missed in a large and unwieldy dataset. This project sought to work alongside current academic and industrial collaborations at the UoB to develop an Artificial Intelligence (AI) and ML system for the enhanced processing and evaluation of "Big Data" derived from a large (and potentially unlimited) number of mobile (and fixed-position) radiological monitoring devices in order to yield a more informed detection response, therefore enhancing the UK's current national radiological surveillance provision.

Detector Data Assimilation

To utilise the greatest amount of existing, new and future radiation sensor data (both static and dynamic), a "pipeline" was constructed through which the differing device output formats were fed into the Amazon Web Services (AWS) repository system – in this instance, AWS S3 Bucket via IoT Core and AWS Greengrass. As part of this workflow, a number of corrections and calibrations were performed, labelled 1 to 5 in the schematic below, facilitated by the low-cost m5stack device. It was only once comparable detector data was available on the cloud could any deep-level analysis be undertaken.

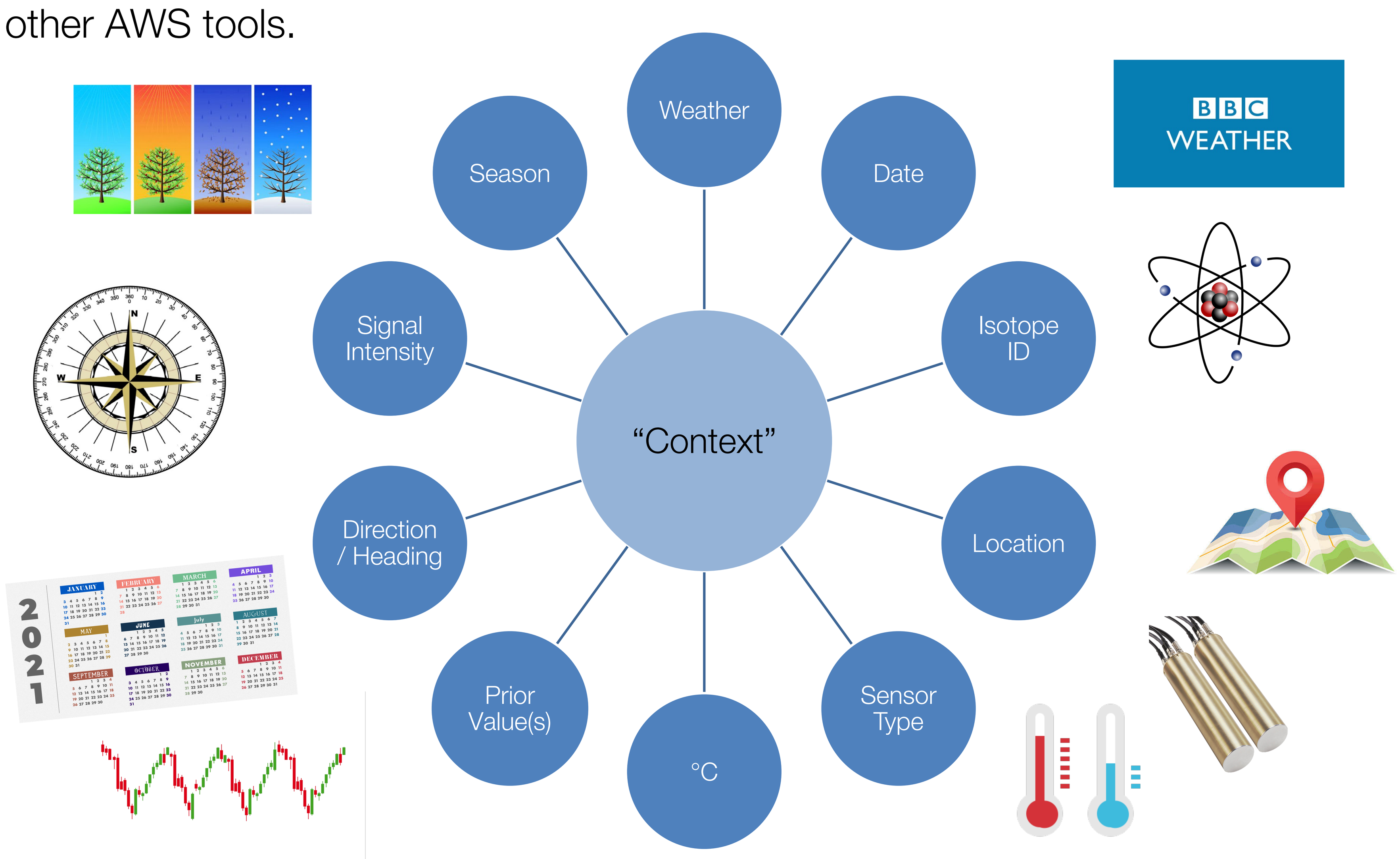


[Above] AWS m5stack™ micro-computer device.

[Above] Schematic of the detector input workflow, with raw detector data processed through a calibration and unification pipeline to allow for subsequent deep-level analysis and the application of AI and ML functionality.

Contextual Data Incorporation

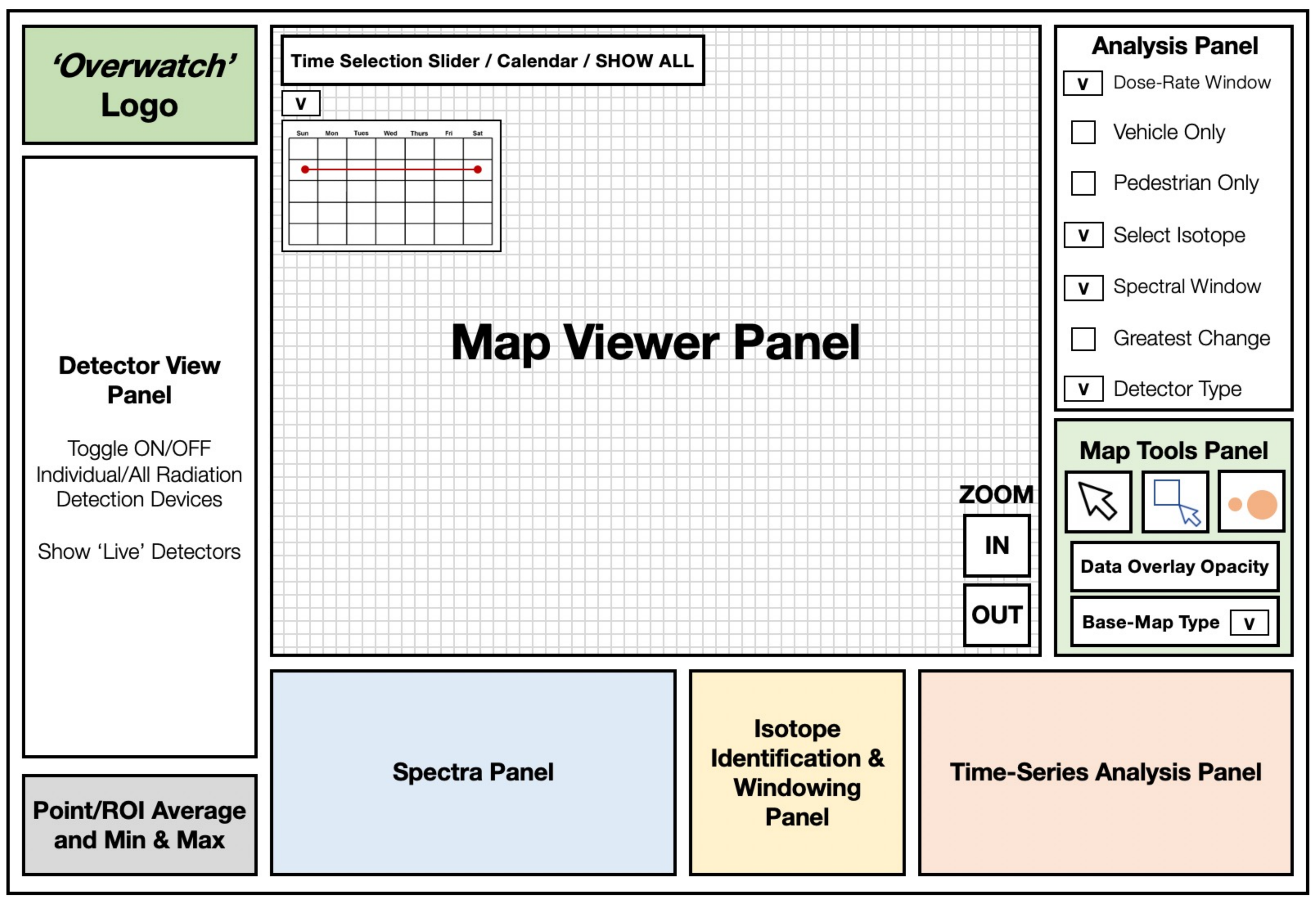
In order to understand, detect and interpret any meaningful changes within the underlying data (that has now been made directly comparable through the prior processing workflow), additional sensory, environmental and contextual data is also incorporated with the radiometric data in the AWS S3 Data Bucket via SDK and API toolkits into external data sources – such as BBC Weather, pollution statistics, Google Maps Traffic and climatic models, to name but a few. Having amassed such a rich and expansive "Data Lake", it can now be interrogated via other AWS tools.



[Above] Representation of the additional data fields that are incorporated into the AWS S3 Bucket to form the multi-variable "Data Lake" upon which AI and ML models can be run.

Graphic User Visualisation & Interpretation

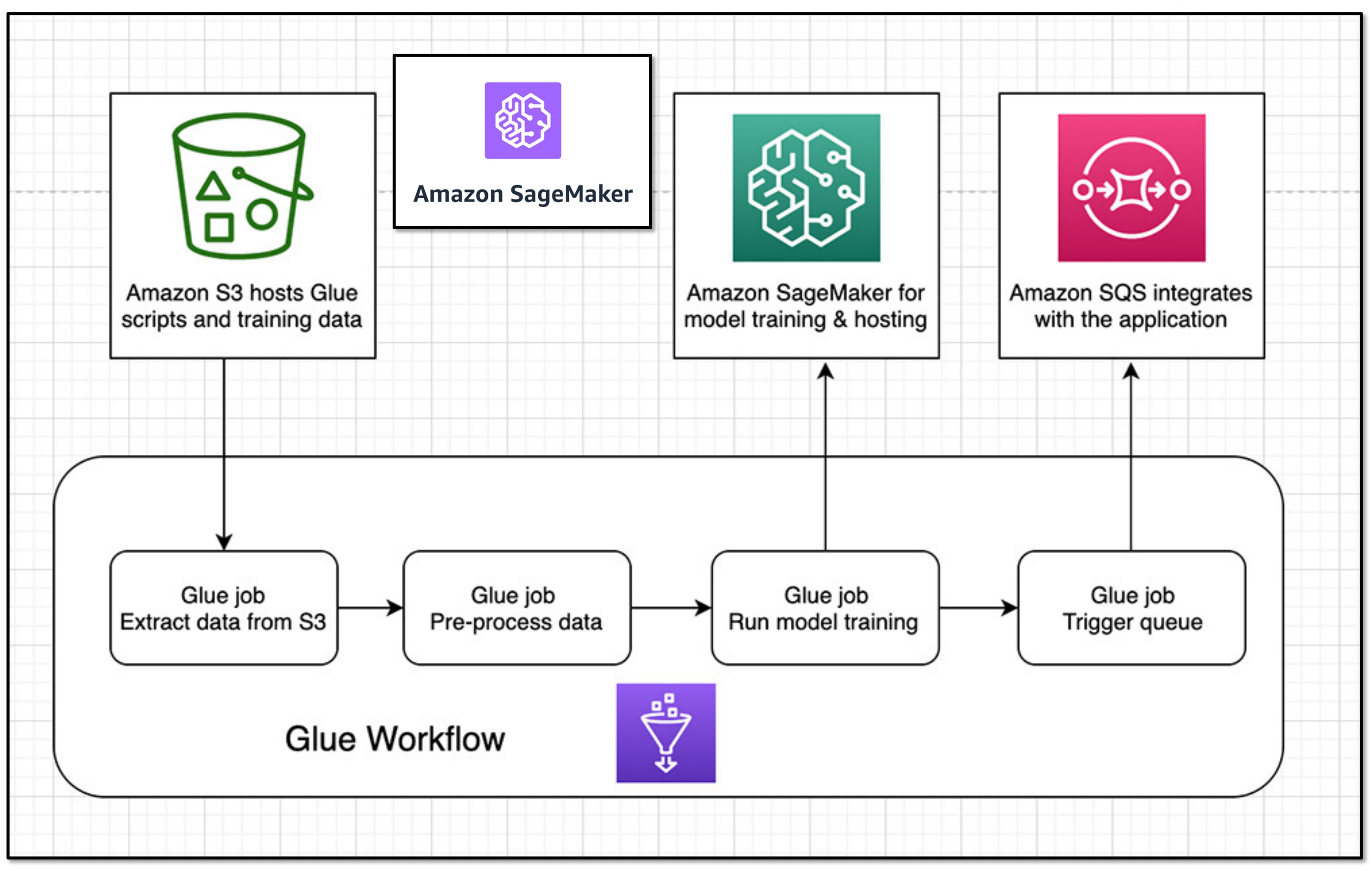
The resultant data, alerts and analysis is nothing unless it is adequately displayed for the user to visualise. With the assistance of ESRI, we have begun developing a web-based portal through which both raw and AWS-processed data and results are plotted in real-time – interrogating the backend "Big-Data" repository held within the AWS (S3 Bucket) Cloud via SQL "AWS Glue" query.



[Above] Screenshot of the design for the ESRI 'Dashboard' through which the backend AWS data is interrogated and associated analysis simultaneously visualised. Through this secure web-based console individual sensors can be toggled on/off and spectral data (including isotopic identifications) viewed. AI and ML can also be run on sub-sets of selected data.

Artificial Intelligence and Machine Learning Implementation

The vast AWS environment features over 220 cloud-based tools for a range of applications, with the Machine Learning tools being some of the most advanced and flexible for tailoring to specific end-user applications. In this work, the "AWS SageMaker" tool was used, employing a number of specific 'task' modules that are available from the AWS Marketplace to expedite the construction of the initial AL/ML capability. After training the model with known 'trigger' and 'non-event' datasets, the system was left to self-learn and build the model independently.



[Above] Schematic of the AWS SageMaker workflow, with the multiple datasets held within the S3 Bucket (assimilated via Glue) before being processed ready for subsequent interrogation. The application of AI and ML was able to identify long-range and external variable dependent trends within the data that would have otherwise resulted in anomaly alarm activations.

Conclusions & Future Work

Although at an early stage of development and with comparatively few sensory inputs to facilitate the greatest level of ML and AL analysis, this work to design and implement a more intelligent radiation detection and enhanced alerting capability by incorporating increasingly advanced (yet user-intuitive) cloud-based AI and ML tools has shown great promise during this NuSec Pilot Project. By contextualising radiometric data alongside other sensory and environmental data streams, as well as better analysing the spectral data derived from each of the distributed detector 'nodes', the number of false alarms requiring investigation has shown to be significantly reduced - resulting in considerable time, resource and cost savings for the end user. Future work will seek to increase the volume of detector nodes feeding into the secure "Overwatch" detector network, alongside enhancing the AWS-based AI/ML functionality by further model training using additional contextual datasets.

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