Monitoring irradiated bismuth targets using machine learning model

Andrew Blades, Gabriel Tabacaru, Samuel Apata, Lauren McIntosh, and S.J. Yennello

Astatine-211 (^{211}At) is a radionuclide that is being studied for its potential use in cancer treatments such as Targeted Alpha Therapy (TαT) [1]. To create ^{211}At, Bismuth-209 (^{209}Bi) is bombarded with α-particles with an average kinetic energy of 28.8 MeV via the ^{209}Bi(α,n)^{211}At reaction. The production cross section for ^{211}At is presented in Fig. 1. The high energy of the α particles generates a large amount of heat on the bismuth target, which can melt the bismuth and cause radioactive ^{211}At to volatilize. If this occur, extraction is more difficult and dangerous.

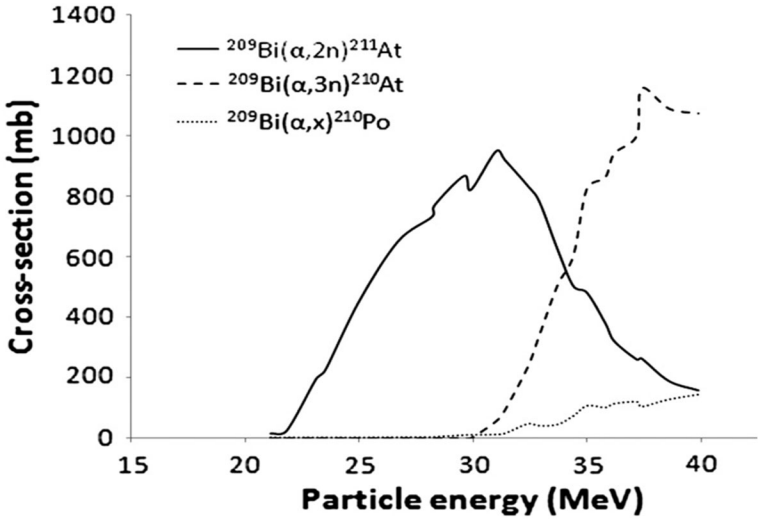

Fig. 1. Cross section of ^{209}Bi as a function of α-particle energy [Ref.2].

Even with active cooling, the bismuth target must be monitored at all times for signs of melting. While it is possible to have a human observe the target through a video camera during irradiation, it is impractical and an inefficient use of resources. Human observers are subject to external influence, can get distracted, and are less capable of noticing gradual visual changes over time. Instead, an automated system has been designed to take the place of the human observer and perform the task without fatigue or distraction.

This task is achievable through training a machine-learning (ML) model to visually analyze the target. By providing a series of categorized images (melted and unmelted) to a Keras Tensorflow model training program, an algorithm was developed and integrated into a Python program capable of feeding the model live images for real-time analysis. This program is capable of running indefinitely while displaying current data analysis information about the bismuth target.

This year, we took an existing ML model and produced a reliable monitoring program. In the past, the monitoring program crashed the computer that it ran on, leading to a critical loss of data that was necessary for estimating the yield of the target. These crashes were a result of the resource-intensive nature of ML algorithms due to the millions of parameters (weights and biases) required to perform complex visual analyses [2]. Through a careful and thorough process of optimization, a program capable of running with

stability and lower resource consumption was developed. Reducing resource consumption required two steps.

First, the algorithm needed to be trimmed of excess parameters. Unnecessary parameters increased computational overhead without improving model performance. The number of parameters was reduced from 3.7 million to 1.4 million. Additionally, optimizations were made to the code to prevent repeated loading of the model from storage into memory.

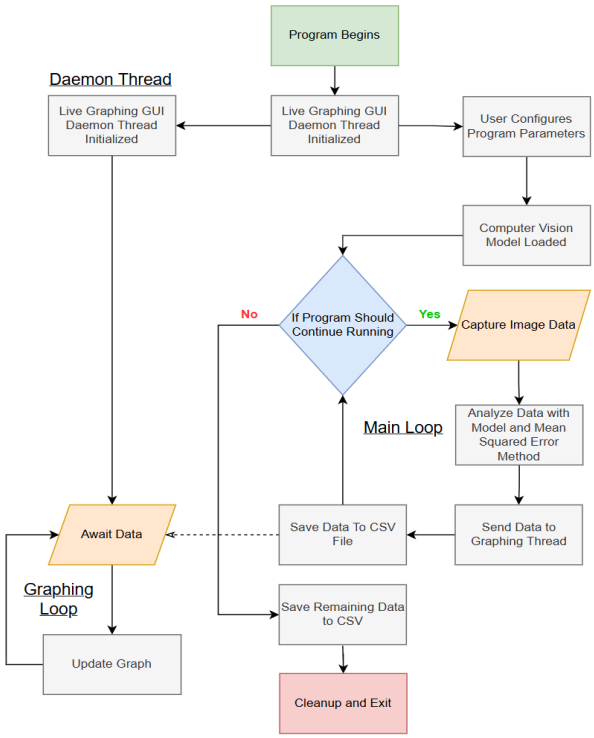

Fig. 2. Flowchart illustrating the multi-threaded Python program designed to enable the use of Deep-Learning computer vision.

Second, the original Python program(s) intended to utilize the model were rewritten from the ground up. Multiple scripts were initially used so that data could be read, written, and displayed at the same time. Unfortunately, shared access to the same data introduced race conditions, leading to read/write conflicts and system crashes. To resolve this, the programs had to be altered and joined together into a multi-threaded program, allowing for equal flexibility but safe data access. This greatly improved the stability of the program, enabling its use in live irradiations.

During the first ^{211}At run at Texas A&M of 2025, this program ran on two separate occasions, from 04/28-04/29 and 04/29-04/30. It proved stable during both and was able to run alongside other programs without conflicts or crashing during both of its ~10 hour uptimes.

These initial runs also provided a valuable dataset for future training. With the recorded melt events and model responses, the next goal of development will involve re-training the model under simulated melt conditions, followed by validation using the newly acquired data.

[1] F. Guérard, F. Gestin, & M. W. Brechbiel, Production of [^{211}At]-Astatinated Radiopharmaceuticals and Applications in Targeted α-Particle Therapy. Cancer Biotherapy & Radiopharmaceuticals, 28(1), 1 (2013). https://doi.org/10.1089/cbr.2012.1292
[2] Francois Chollet, Deep Learning with Python, Second Edition , Manning, 2021.