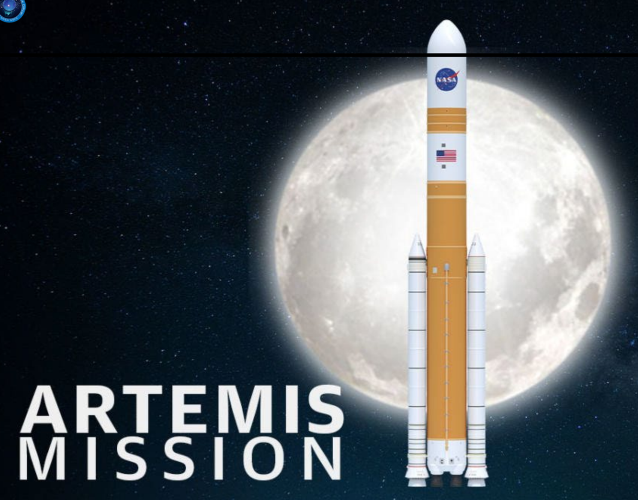


Autonomous Detection and Classification of Lunar Minerals Using a Convolutional Neural Network Based Framework for the SUCR DALI Project

Noah Carter[1,2], Eric Z. Tucker[2], Michael Grant[2], M. N. Abedin
[1]George Mason University, [2]NASA Langley Research Center

National Aeronautics and Space Administration

ABSTRACT

NASA's long-term goal is to deploy humans to the Moon and, from there, advance **human** exploration to Mars, with Artemis missions as pivotal milestones. Raman spectroscopy can uniquely identify minerals, compounds, water states, and other materials, providing distinctive fingerprints for classification. A Raman instrument has been successfully deployed and utilized on the Mars surface via the Perseverance rover, but has not yet been utilized at the lunar surface

The **SUCR DALI** project is working towards developing a Raman spectroscopy instrument to be applied in various lunar mission concepts, including within the Artemis program.

The objective of my research is to assist in the maturation of the proposed SUCR DALI lunar Raman instrument through the development of an autonomous detection and classification model capable of identifying minerals and water states on the Moon's surface.

INTRODUCTION

Key Exploration and Science Resource:

The lunar regolith holds billions of years of history, rich in resources that will fuel the Artemis Program's mission to sustain life, drive innovation, and uncover the Moon's geological secrets.

Researchers at Langley Research Center have been developing a portable Raman instrument, the Standoff ultra-compact Raman (SUCR) sensor, which was previously advanced to a breadboard state. Through a recently awarded DALI proposal, the team has been working to advance the TRL beyond its breadboard configuration towards a flight-ready system, although a flight-ready system is beyond the scope of this proposal [2]. To this end, **we have developed an initial algorithm that has been able to autonomously classify lunar materials.**

Previous research has shown that a convolutional neural network (CNN) performs the best for classifying materials in spectroscopic data, which is aligned with our use case [1]. The neural network analyzes structured data and can treat spectral data like an image to pass filters through.

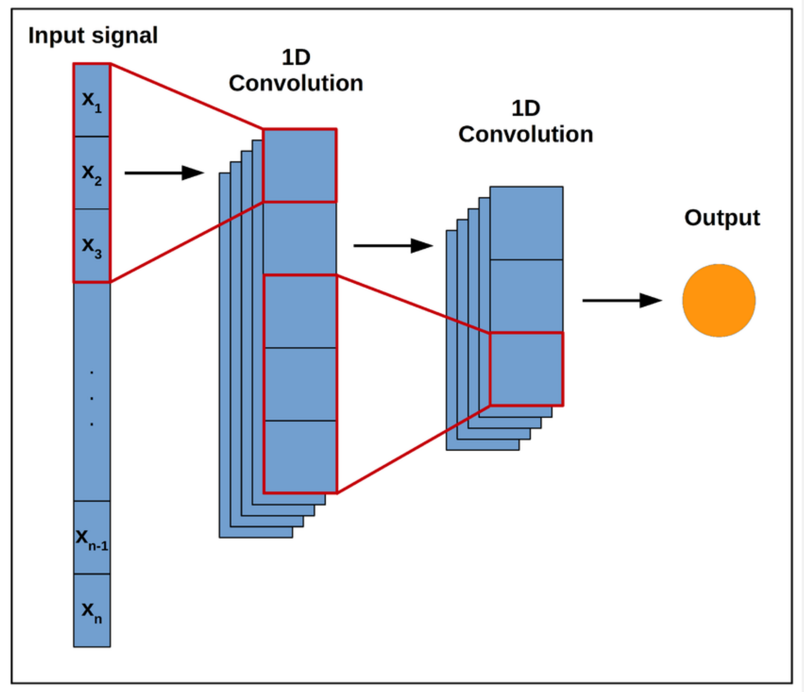


Figure 1 shows a schematic of a CNN operation

Figure 1 shows a schematic of a CNN operation. This enables the CNN to learn important patterns through intensity points and peak trends for classification by passing filters. However, it is important to know how the model will learn to avoid complications.

METHODS

First, we established a raw spectral database for training our model, taking care to have a diverse range and large enough set of data, then we interpolated wavenumbers and normalized intensity values for better pattern readability.

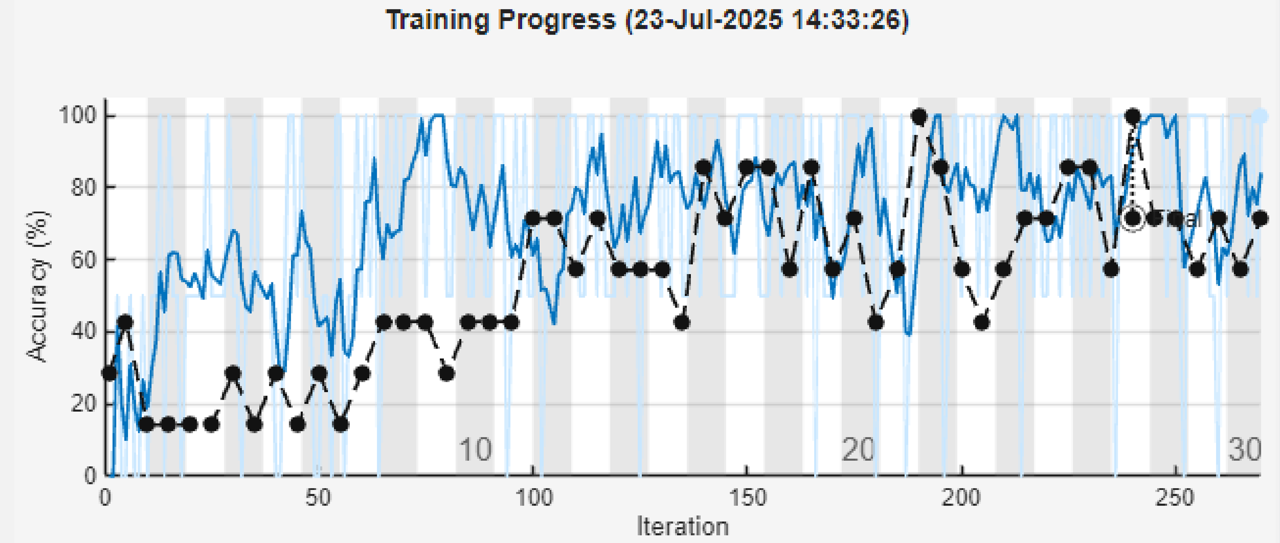
Next, we constructed a CNN structure in MATLAB. The process started with an image input layer; however, the 4D size did not work well with 1D input in. Finally, the sequence input layer proved to work best, creating a proper 1D input layer that was perfect for spectra sequencing [3].

Currently, a 5-mineral multiclassification task from mostly pure samples is the initial approach we have started to work on. Due to the complex nature of the "fingerprint" patterns the model needs to learn and identify, we have adopted a 3-block convolutional structure designed to capture important features: broad, medium-scale, and fine spectral characteristics through adjusted window sizes and filters for refinement in each block.

Challenge: In the early stage of research, the broad range of features detected from 4,500 intensity values meant that a single window and filter range could not capture all the important features. This resulted in the early detection model achieving a validation rate of only 23.5%.

Shown in Figure 2, we see a training progress plot created to display accuracy. With the 3-block CNN structure capturing a diverse range of spectral features, we have managed to improve the accuracy from a validation rate of 23.5% to 71.43%. This is a significant advancement, especially considering the minimal data used in the training set.

Figure 2 Plot of accuracy during training of the 3-block CNN which shows a validation rate of 71.43%.



RESULTS

From the model we developed, we successfully classified minerals based on the Raman data. As shown in Figure 3 we successfully classified an unknown spectrum as sulfur. The model used for classification of Figure 3 was trained on binary classification between sulfur and naphthalene. The model was able to identify key Sulfur "fingerprints".

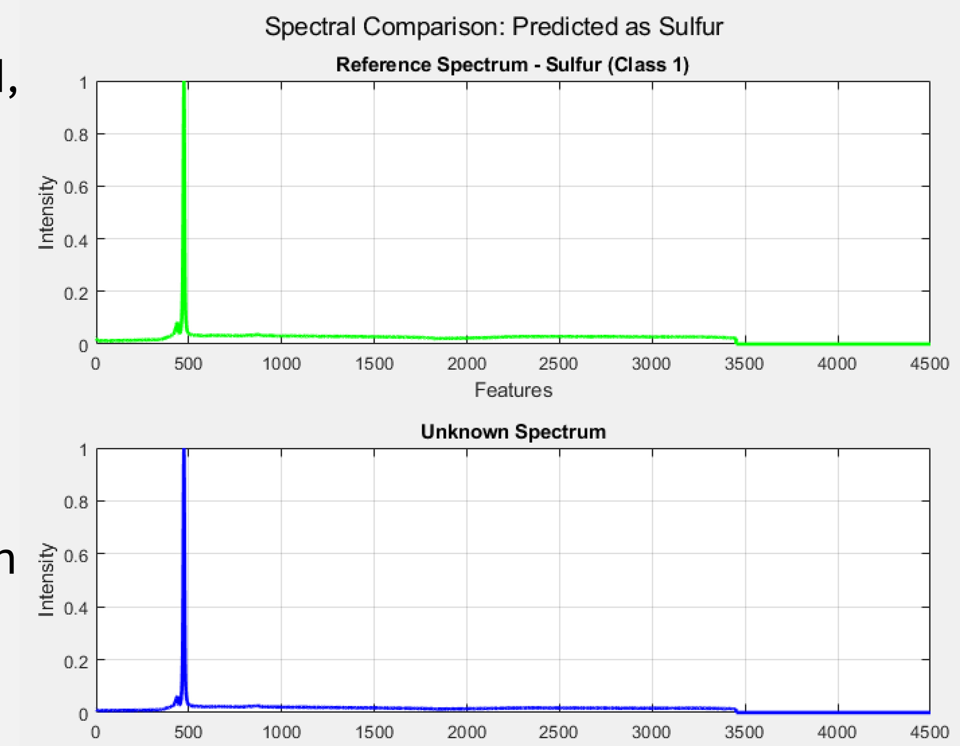


Figure 3 (Unknown spectra classified.)

CONCLUSIONS

The development of a reliable classification model contributes to advancing autonomous exploration capabilities for future lunar missions. Additionally, optimizing a 1D CNN sequence input layer for Raman spectral data processing using MATLAB's Deep Learning toolbox is a notable technical milestone achieved during this research.

FUTURE WORK

Future work will involve additional binary classification tests to identify which minerals require more data based on spectral patterns and complex sequences. Over time, we can implement the detection of constituents in samples containing more than one mineral, enabling the model to identify multiple minerals within a single spectral scan, as well as water states.

Other future work will involve the possibility of adding noise to existing data in the database to augment the number of training data and spectral diversity, which should improve model accuracy and generalizability.

As the model's knowledge grows, the ultimate goal will be to recode the MATLAB script into C and implement the software on an FPGA for high compute performance.

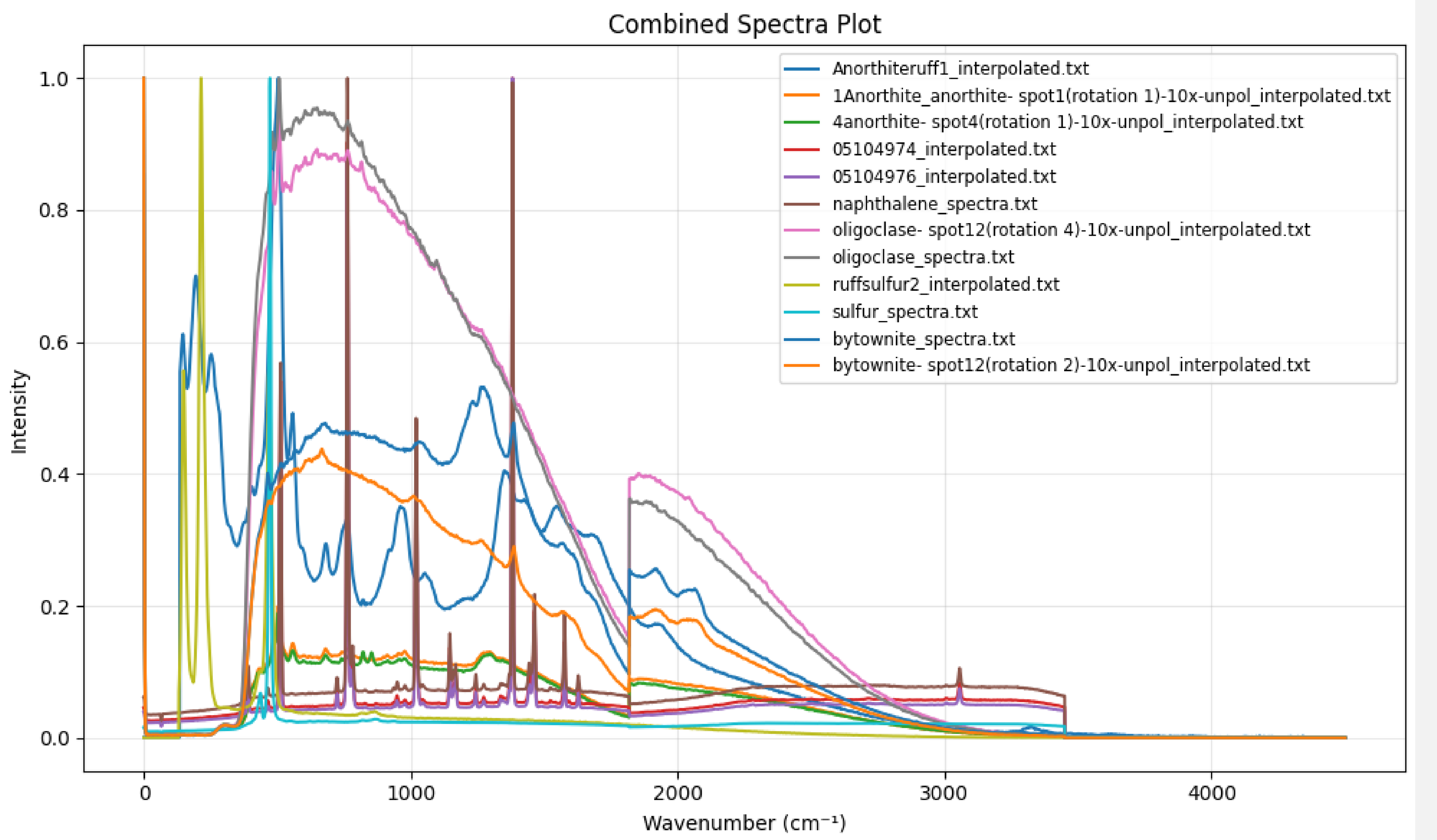


Figure 4 Spectral plot of several minerals

Looking at Figure 4 above, we have several different spectra to provide a comparison of the spectral patterns the model will need to learn. However, the goal is for the algorithm to be able to classify over a thousand different lunar inorganic minerals on the surface of the moon.

REFERENCES

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