of plants, animals, and minerals, and even extended this systematic approach to diseases (Linneaus, 1758). Preceding Linnaeus, however, the concept of a natural order can be traced back as far as Aristotle's *Scala Naturae*, or*Great Chain of Being*, which sought to arrange all living organisms in a linear hierarchy (Aristotle, 350 B.C.E).

In the realm of geology, various methods are employed to classify rocks by appearance, composition, or other criteria. For instance, in petrology, labels like "igneous", "sedimentary", and "metamorphic" form the foundation for classifying rocks into categories by formation process (Blatt et al., 2006). Each of these broad categories contains its own subdivisions and methods of classification. In igneous rock classification, for example, methods include categorization based on grain size, differentiating between coarse-grained intrusive and fine-grained extrusive rocks, as well as by composition into felsic, intermediate, mafic, and ultramafic groups (Turner et al., 1951). In sedimentary contexts, rocks are classified as clastic or chemical/biochemical based on their origin. Clastic rocks are then subdivided by grain size, from coarse conglomerates to fine siltstones and shales (Tucker, 2009). And in metamorphic contexts, rocks are classified by their degree of foliation, ranging from slate to gneiss, and by their parent rock, like basalt or limestone (Turner et al., 1951). Such systemic categorization helps bring order to the diversity of natural materials, and, in the context of geology, often shines new light on formation and alteration processes. Classification provides the vocabulary and building blocks that facilitate the generation and testing of hypotheses which, in turn, advance the field.

In this paper, we introduce an image classification methodology that aims to reduce reliance on domain expertise, is applicable to datasets too small for effective machine learning utilization, minimizes classifier bias by using terms without process connotations, and is both flexible and scalable. Here we use "classifier bias" to refer to the inherent assumptions or prior beliefs influencing the classifier (Izadinia et al., 2015; Sun et al., 2020). Our method is grounded in first-principles philosophy, employing simple, unambiguous, and universally comprehensible image descriptors: simple, intuitive visual features, such as tonality or texture, that can be easily recognized and agreed upon by observers without specialized training (c.f. Haralick et al., 1973, Tamura et al., 1978). Our method is built on the following assumption: that by responding to a series of binary (yes/no) questions concerning an image's elementary visual features, one can construct a nuanced description for the image, even without prior exposure to similar images. This approach has significant implications for enhancing the objectivity and efficiency of image classification across diverse datasets. To showcase the effectiveness of this methodology, we organize a set of NASA *Curiosity* rover ChemCam images into visually similar groups. However, this method is not intended solely for Mars rock image classification. We theorize that this same general method could be applied successfully to almost any image dataset.

1.1. NASA's curiosity rover and ChemCam

NASA's *Curiosity* rover landed in Gale crater, Mars, on August 5th, 2012. Gale crater is an ≈155 km wide impact crater on the boundary of the Southern Highlands and Northern Lowlands dichotomy in equatorial Mars (Anderson, 2010; Grotzinger et al., 2014). The interior of the crater hosts a wide variety of rock types, including lacustrine, fluvial, and eolian deposits rich with diagenetic features, as well as igneous material often observed as float rocks (Banham et al., 2018; Cousin et al., 2017; Edgar et al., 2020; Fraeman et al., 2016; Grotzinger et al., 2014, 2015, 2012; Milliken et al., 2010; Stack et al., 2019; Vasavada, 2022; Vasavada et al., 2014).

Over the last decade, various classification methods have been developed with the aim of sorting these rocks into process-oriented facies. Such classifications have helped establish and support new ideas about ancient processes on Mars. For instance, Mangold et al. (2016) used *Curiosity*'s ChemCam and Alpha-Particle X-ray Spectrometer (APXS) instruments to identify two classes of conglomerates from the Darwin and Kimberley locations, respectively, providing new insights into igneous crust composition and diagenetic processes. Cousin et al. (2017) classified 59 igneous rocks from a broader region of the crater floor into five groups based on their textures and compositions, ranging from basalts to trachytes and quartz-diorites, which led to the conclusion that fluvial activity could have transported some of the alkali-rich rocks from the northern crater rim. Sun et al. (2019) documented four main concretion assemblages within the Murray formation and correlated them with specific chemical enrichments, which helped reveal multiple fluid events and late-stage diagenetic processes.

These studies and others have furthered our understanding of Mars' geologic history but also highlight the challenges inherent in accurate rock classification. When information is limited to images and chemical composition, process-oriented classifications can risk introducing classifier bias. The challenge of bias-free classification raises the following question: **How can we classify a broad selection of rock types without introducing assumptions and/or interpretations about the processes that brought the rocks to their current state?** To answer this question, we propose a classification system grounded in the recognition of simple, visual characteristics. Though developed here in the context of Mars rock images, the first-principles philosophy underpinning this classification system gives it the flexibility to be adapted to a wide range of image datasets, potentially promoting more objective and unified analyses across various scientific disciplines.

2. Methods

Since landing, *Curiosity* has driven more than 30 kilometers up the slope of Mount Sharp, exploring for more than 4000 martian solar days (sols) (Grotzinger et al., 2014). In the past 12+ years, *Curiosity*'s ChemCam has observed thousands of rock targets. During the first martian year of its mission, *Curiosity* explored the Bradbury formation, an ancient fluvio-lacustrine deposit (Grotzinger et al., 2015). Our dataset (Essunfeld et al., 2024) consists of 201 images of high-Mn ($\geq$ 0.20 wt% MnO) rock and soil targets captured by *Curiosity*'s ChemCam Remote Micro Imager (RMI) in the Bradbury region of Gale crater. These images were post-processed with complementary data from Mastcam, a stereo RGB camera system located on the mast of the rover along with ChemCam (Malin et al., 2017; Maurice et al., 2012). We documented the visual characteristics of these images, creating numerical labels for each image, and then grouped similar image labels using multiple network algorithms, as we will discuss in the remainder of the paper.

2.1. ChemCam and Mastcam

Curiosity's ChemCam instrument uses Laser-Induced Breakdown Spectroscopy (LIBS) to obtain chemical composition data from rock targets (Wiens et al., 2012; Maurice et al., 2012). In conjunction with each LIBS analysis, high-resolution[1] greyscale images of rock targets are taken by ChemCam's Remote Micro Imager (RMI), and wider-view,[2] color images are taken by the rover's Mastcam instrument (Le Mouélic et al., 2015; Malin et al., 2017). These images are post-processed together, resulting in a high-resolution colorized RMI mosaic (hereafter simply "image") for each rock target. In general, each ChemCam target has an associated colorized RMI mosaic (Le Mouélic et al., 2015; Maurice et al., 2016). However, for some very early mission targets, Mastcam images were not taken in conjunction with the mosaic. We were able to obtain colorized mosaics for ≈90% of our 201 targets and had to use greyscale mosaics for ≈10% of the targets. It should be noted that using greyscale mosaics did not significantly affect our analysis, as we did not document color directly in our classification.

[1] ChemCam's RMI can resolve 1 mm features at 10 m distance

[2] ChemCam's RMI has a FOV of ≈1° while Mastcam's cameras have FOVs of ≈5° and ≈15°.