Over the past few decades additive manufacturing has transformed from a technique used only for rapid prototyping to one of the primary manufacturing techniques used in research and industries pertaining to its ability to create intricate shapes, waste minimisation, and design freedom. Despite significant advances in AM techniques for materials across the spectrum, additive manufacturing for metallic alloys is still in its relatively nascent stage of development. Significant strides towards developing highly optimized techniques for metallic alloy systems are also limited by the presence of enormous phase space for designing alloys which leads to varied final microstructures and thus mechanical properties even for slightly distinct alloy compositions. Nonetheless, previous studies conducted on a wide range of alloys to investigate the reasons for failure in them have pinned down the prominent reasons for failure being either porosities or residual stresses. Further the porosities have also been classified into two categories: lack of fusion and gas pores. This classification is based on their morphology and factors which give rise to them. Further, multiple studies have also shown these defects to be the crack initiation and propagation sites which reduces the lifespan of AM components. The lifespan of AM components have also been depicted to depend on the distribution of these defects and stress field on the fracture surface. Hence our ability to analyze fracture surfaces and identify features on them along with their distribution dictates our ability to understand the process through which a component fails. This helps us devise ways using which we can optimize process parameters to enhance desired mechanical properties of our component. So, the aim of this work is to devise a generalized technique using Machine Learning and with minimum human intervention to perform quantitative segmentation of Fractographs of AM components with multiple different fracture features.

Generally, Fractures can be classified into three different types: Ductile, Brittle and Fatigue. However, for the current research work we will consider only Ductile (Dimples), and Brittle(Cleavage). We will further classify the ductile class into Normal Dimple and Sheared Dimple. For the current work, we will be doing fractographic analysis on Ti-6Al-4V alloy, which is prepared using additive manufacturing and fractured. Fractographic analysis using supervised machine learning may yield good results, but only for some specified materials as these algorithms usually fail in performing predictions on microscopy images of material systems with morphological and microstructural characteristics that deviate substantially from the common known morphological form of them, this is when human intervention can introduce errors/bias. Here comes the need for the classification of different types of fractures, based on features that a fractured surface usually has. Instead of training the model with some human annotated images as supervised learning does. We shall use an unsupervised learning algorithm that will only make use of the likelihood of a particular feature belonging to one fracture class calculated using a mathematical model . To accomplish this work, we will make use of a combination of unsupervised machine learning algorithms and feature engineering. Unsupervised machine learning can overcome the above mentioned limitations and enable inference on microscopy images from a broader range of material systems. While with the addition of feature engineering, we can leverage the data to create new variables that aren't in the training set. Some features that we will be making use of are diameter, maximum depth, coefficient of roundness, etc, of individual objects on the fractographic images. Unsupervised machine learning has been previously used in fractography for the classification of fracture surfaces of five tungsten rich alloys according to their chemical content, and authors arrived at reasonably good results. These results encouraged us to make use of unsupervised learning for the classification of different types of fracture.