Deep Learning has made large strides in both supervised and unsupervised learning. The abilities of Deep Learning have been shown to beat both generic and highly specialized classification techniques with little change to the underlying concept. Though this has caused a resurgence of interest in neural networks, many of the drawbacks and pitfalls of such systems have yet to be addressed after nearly 30 years: speed of training, local minima and manual testing of hyper-parameters.

In this thesis I propose using an evolutionary technique in order to work toward solving these issues and improve the overall quality and abilities of Deep Learning Networks. In the evolution of a population of automatic data encoders (autoencoders) for input reconstruction, I was able to abstract multiple features for each autoencoder in the form of hidden nodes, scoring the autoencoders based on their ability to reconstruct their input, and finally selecting autoencoders for crossover and mutation with hidden nodes as the chromosome. In this way I was able to not only quickly find optimal feature sets, but also optimize the structure of the autoencoder to match the features being selected. This also allowed me to experiment with different training methods in respect to data separation and selection, reducing overall training time drastically for large and complex datasets. This proposed method allows even large datasets to be trained quickly and efficiently with little manual parameter choice required by the user, leading to faster, more accurate creation of Deep Learning Networks.