ABSTRACT

Although metasurfaces provide unparalleled design flexibility, finding optimum structures remains a difficult challenge for which Deep Learning approaches are becoming increasingly important. In this study, new neural architectures are explored that go beyond the commonly used feedforward designs and investigate their use in the construction of multiple-element metagratings. Increasing the number of layers is ineffective with sophisticated datasets because the vanishing gradient makes it more difficult to train, resulting in saturated or decreased predictability.This problem is addressed by residual learning (ResNet) [12], which identifies shortcuts that transmit the gradient by skipping one or more layers .By directly linking all layers in DenseNet, identity mappings are further utilised , which not only alleviates the vanishing-gradient but also enhances feature propagation by reusing them. Furthermore we investigate the Active learning techniques for regression analysis to curate small datasets to train the architectures and provide accurate prediction with less training samples.Lastly we measure the efficacy of surrogate-based evolutionary optimization(Differential Evolution) is used to assess the utility of surrogate models. Models are generally evaluated only on the basis of training error and error on similarly sampled testing sets, which may or may not be indicative of their performance throughout the whole design space.

Keywords: Deep learning, Metasurfaces, Active Learning, Residual Learning, Differential Evolution