Deep Operator Networks (DeepONets), have been successfully applied to many engineering problems where a full-field solution contour is learned by the network based on the provided inputs, and is able to generate almost instantaneous predictions of full-field solutions. The classical DeepONet architecture uses a branch network to encode the input functions, and a trunk network to encode the problem geometry. The encoded outputs are combined to form the network output via a dot product. In this talk, we introduce three different DeepONet architecture variants that are specialized in capturing varying input geometries, time-dependent applied loads, and predict multiple time steps of the output fields, respectively. We demonstrate their effectiveness by three case studies and compare their performance with a baseline DeepONet model with a feed-forward neural network in its branch and trunk networks.