*Source 1 is* [*https://www.youtube.com/watch?v=6k4CiNI\_-SQ*](https://www.youtube.com/watch?v=6k4CiNI_-SQ)

Autoencoder: input x with 1-to-1 pixel to layer matching. All hidden layers and new layers are connected as per standard MLP definition.

Stacking Autoencoder

Methods:

Ladder-wise pre-training

End-to-end pre-training: “all in one go”

Cascade multilayer positron (MLP)

*Source 2 is a hands-on with stacked autoencoders with MNIST dataset is* [*https://www.youtube.com/watch?v=tyaA7xbGMG4*](https://www.youtube.com/watch?v=tyaA7xbGMG4)

^ pytorch

*{Sources 1 and 2 are from a youtube channel called deep learning for visual computing – iitkgp}*

{Authors are available here, as their github repository is here: <https://github.com/iitkliv/dlvcnptel>}

Rachana Sathish and Aupendu Kar

*Source 3 is Xu et al from 2016*

Automated nuclear detection is a critical step for a number of computer-assisted, pathology-related image analysis algorithms such as automated grading of breast cancer tissue specimens.

The Nottingham Histologic Score system is highly correlated with the shape and appearance of breast cancer nuclei in histopathological images. However, automated nucleus detection is complicated by two variables: (1) features of nuclei samples including the large number of nuclei and the file sizes of pathology images rendered in high resolution; (2) variation in shape, size, qualitative appearance, and texture of individual nuclei.

Stacked Sparse Auto-encoders (SSAE) provide considerable efficiency given this challenging set of demands, as Xu et al. displayed in 2016.