**Convolutional Neural Network (CNN)**

The challenge of predicting the existence of CHD in patients refers to the task of binary classification. Under certain constraints, neural network has been proven to be an effective parametric classifier under supervised settings. Recently, with the explosion of structured data, deep neural networks incorporating a large number of application specific hidden layers, have demonstrated significant improvement in several areas including speech processing, applications involving image processing, and time series prediction. There is a vast body of deep learning architectures that are fine-tuned and rigorously trained using big datasets. An artificial neural network successively transforms the input data over sequential hidden layers and estimates the error at the output layer. The error is back- propagated to iteratively update the layer weights using gradient descent algorithm. Rigorous experimentations and analyses have proposed several improvements in the gradient descent algorithm, the nonlinearity of layers, overfitting reduction, training schedule, hidden layer visualization and other modifications. Despite resounding success in applications, the working principle of deep neural networks is still poorly understood. It is also found in practice that a deep neural network is extremely susceptible to be attacked by adversarial examples. In addition, owing to millions of parameters in a typical deep architecture, the trained network may be over fitted, especially in cases where there is scarcity of examples. Among various algorithms that attempted to overcome this problem, data augmentation is a widely used technique that artificially generates examples to populate small datasets. However, such a procedure is biologically implausible in most clinical datasets. For example, augmented measurements of a CHD phenotype, such as platelet count, might not correspond to possible readings of a subject. It is because the underlying principles of the statistical generation and the biological sources of platelet count readings may be fundamentally different. Poor training due to small or imbalanced datasets and susceptibility to adversarial examples lead to poor and unreasonable classification. Unlike many computer vision tasks, such as semantic labeling, chat-bot configuration, and hallucinogenic image synthesis erroneous prediction in medical research is accompanied by a significant penalty. For example, faulty prediction of a subject having chronic CHD may leave the subject untreated or misdirect the possible therapeutic medication. Therefore, one of the prime objectives of this paper is to improve classification accuracy, i.e. the prediction accuracy of the subjects with and without the presence of CHD. There are several other relevant concerns related to misclassification in medical research. To overcome these limitations and driven by the success of deep networks, we propose a shallow convolutional neural network, where the convolution layers are ‘sandwiched’ between two fully connected layers