Assisting the Evaluation of Free-body Diagrams using Deep Learning Models

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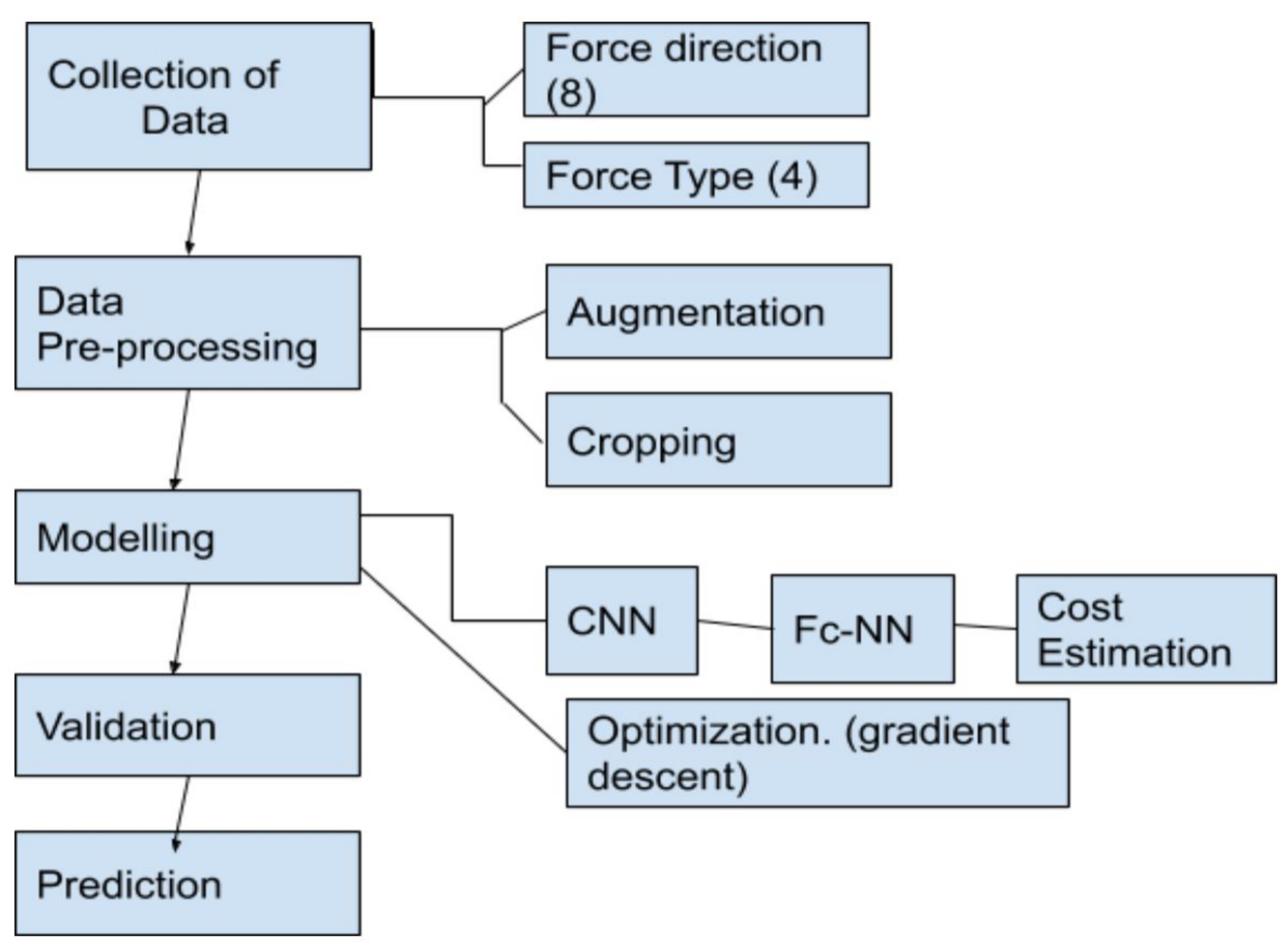
I. Abstract

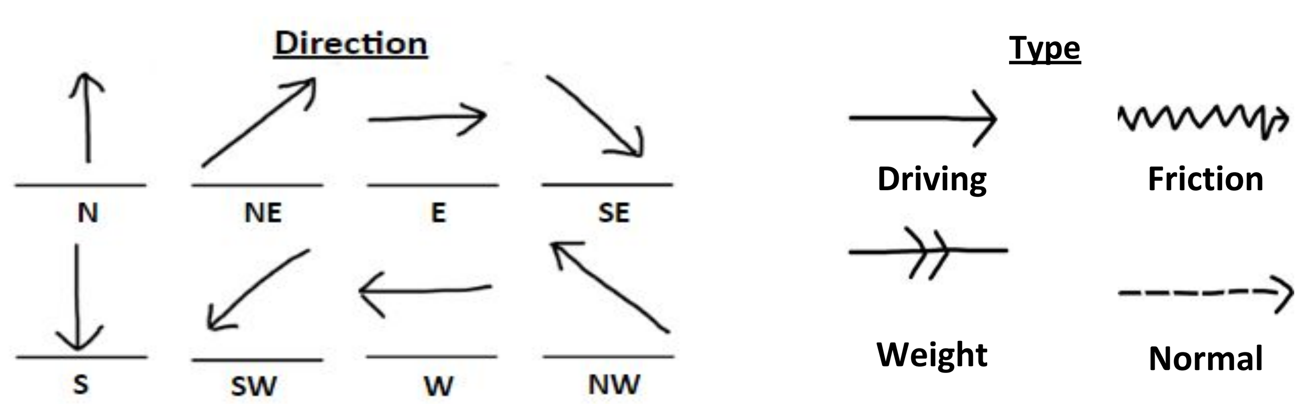
In data science, machine learning uses computer algorithms to build predictive models to make data-driven decisions. Mathematical and computational tools in machine learning have been successfully used, especially in image recognition and classification [1]. In this work, we developed deep learning models to assist the evaluation of hand drawn objects in free body diagrams. Free body diagrams are often used in physics as a way of showing the relative magnitude and the direction of forces acting upon one or more objects. Force vectors are represented in free body diagrams using arrows. First, we developed an image classification model to identify the direction of the force vectors. Secondly, a separate model was implemented to identify different types of forces in free body diagrams. The models will later recognize the important physics in the free body diagram while recognizing the hand drawn symbols such as strings, pulleys and objects. Results show that we were able to obtain a validation accuracy of 97.8% for direction prediction model and 97.3% for force-type prediction model. We have used latest data pre-processing and data-modeling techniques to achieve this performance with minimum number of training images.

2. Method (Steps in brief)

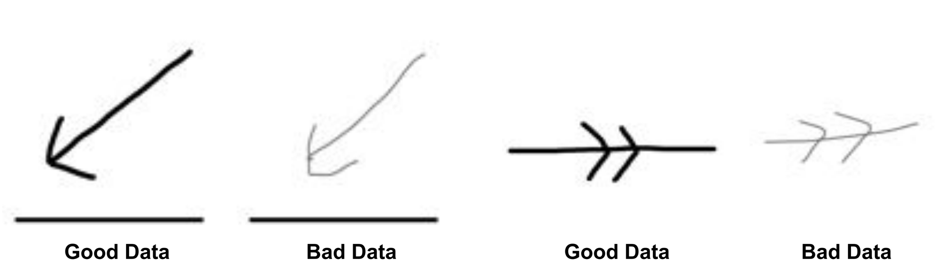


3. Data Set

- We collected data using data collection sheets and within the data set there are two set of classes; one for direction and the other for the type of force.
- There are eight direction classes and four force-type classes. We organize these classes using direction classification and force-type classification.



- Even though some arrows are not drawn as good as others, the models are still able to classify them correctly. Here are some examples for the diverse data instances in the data set:

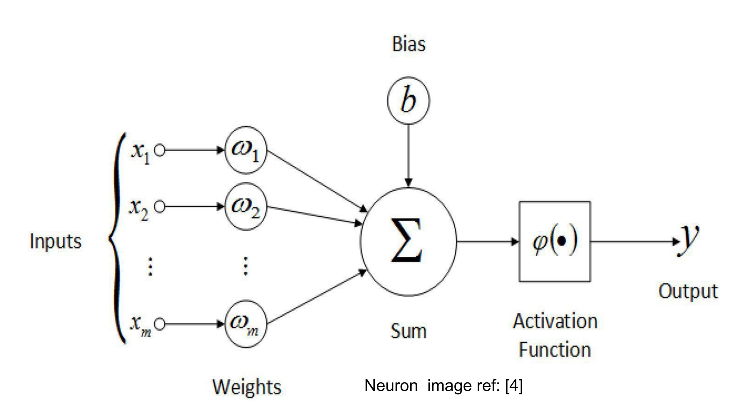


- Since we have a limited number of images, we're going to increase the size using data augmentation. This will be discussed in the 'Data Augmentation' section.

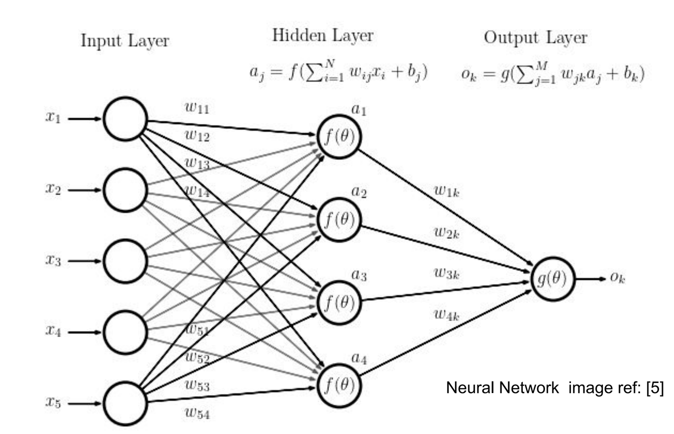
3. Neural Networks

Neural network is a nonlinear hypothesis function used in deep learning. It involves a nonlinear learning process to perform a given task with the help of training examples. Neural networks are comprised of numerous nodes (neurons) that are densely interconnected and organized in multiple layers. A simple neural network structure consists of an input layer, a hidden layer and an output layer.

NEURON



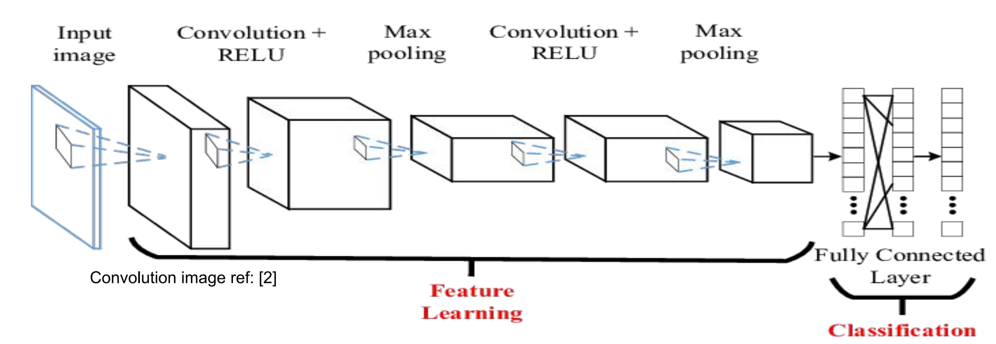
NEURAL NETWORK

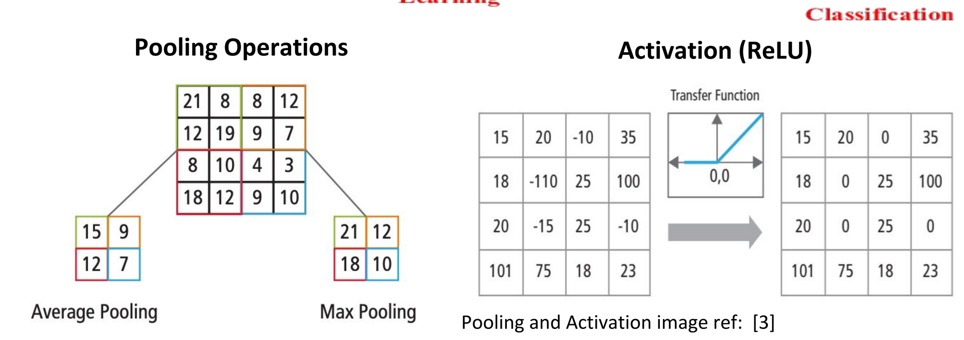


- **The node** takes weighted input, sums them and inputs them into the activation function.
- **The weights** are the real valued learnable parameters. **Bias** is used to adjust input to the activation function independent of the input features.
- **Feed forwarding:** Evaluation of the output from the hypothesis function.
- **Cost Estimation:** Evaluation of the loss using the cost function.
- **Back propagation**: Updating the weights based on the gradient of the cost function.
- **Activation function** is added in order to help the network learn complex nonlinear patterns.

4. Convolutional Neural Networks.

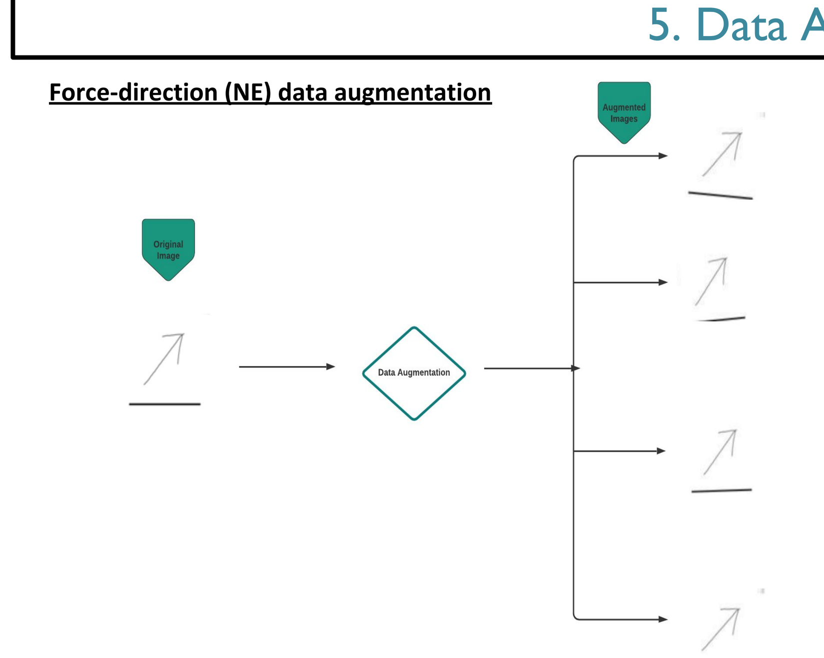
- CNNs are widely used in pattern and image recognition problems as they have a number of advantages compared to other techniques. It can be experienced that when the number of features becomes very large the artificial neural networks do not work well.
- We used CNNs to work with high dimensional data. Or in other words… data with many features.
- CNNs reduce the dimensions while extracting the most important features.

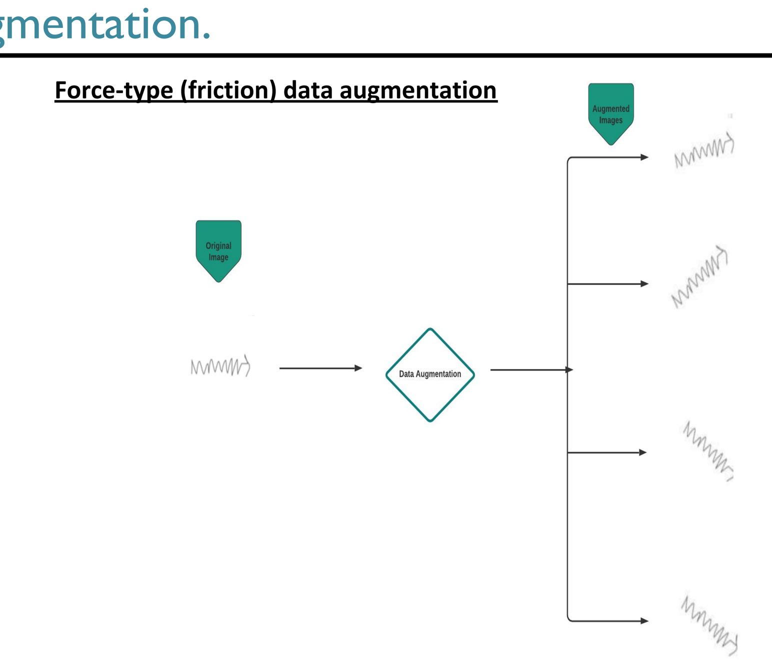




- For both deep learning models (force-type & force direction detection models) implemented in this analysis, we used two convolution layers, each followed by a ReLU activation and max-pooling layer. The fully connected layers for both models consist of one hidden layer with 32 nodes and output layer with number of nodes equal to number of classes. For the convolution layers, 32 filters, each with size 3x3 were used. Implementation of the model was done by deep learning tools available in TensorFlow keras [6].

5. Data Augmentation.





- Data Augmentation done in order to create a large diverse data set by changing the orientation of original data.
- Augmentation Parameters:
  - width shift
  - height shift
  - zoom-in, zoom-out
  - flipping
  - rotation
- Size of the data set was enhanced 10 times for force-direction data and 20 times for force-type arrows

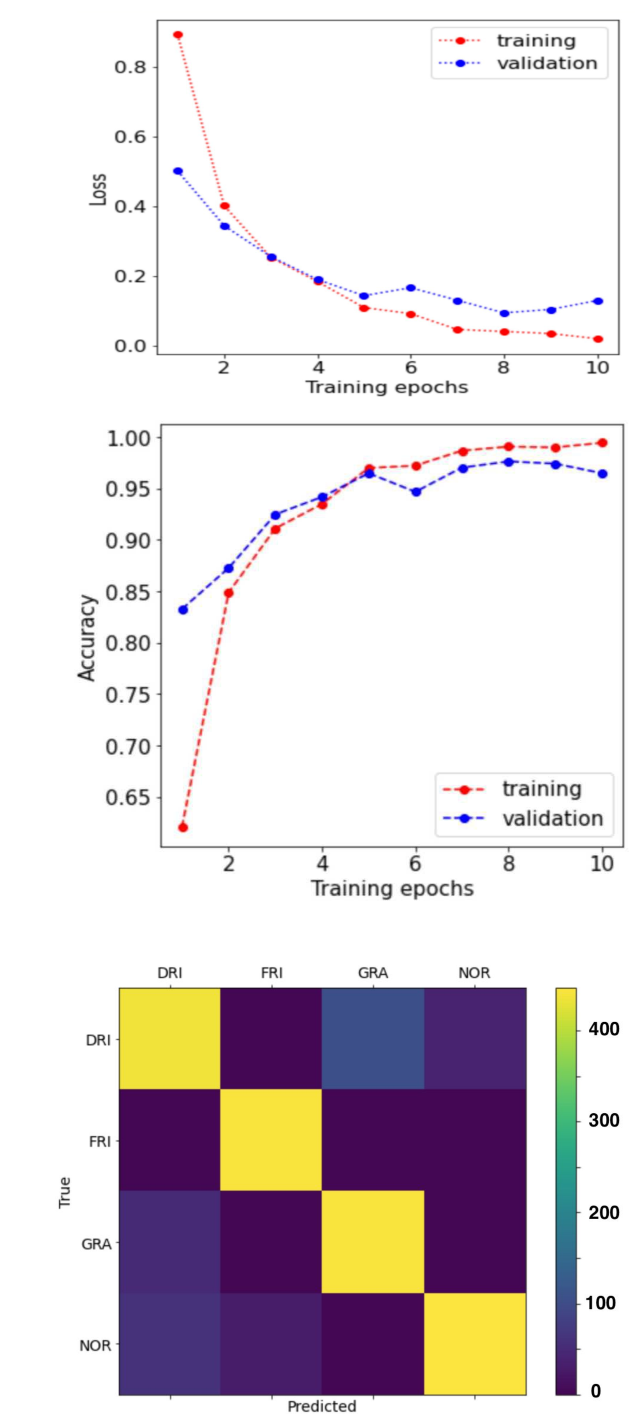
Data Generator for Force-Type Arrows:

```
datagen = ImageDataGenerator(
        rotation_range=40,
        width_shift_range=0.1,
        height_shift_range=0.03,
        shear_range=0.15,
        zoom_range=0.02,
        horizontal_flip=True,
        fill_mode='nearest')
```

6. Results - II (Learning Curves/Confusion Matrix)

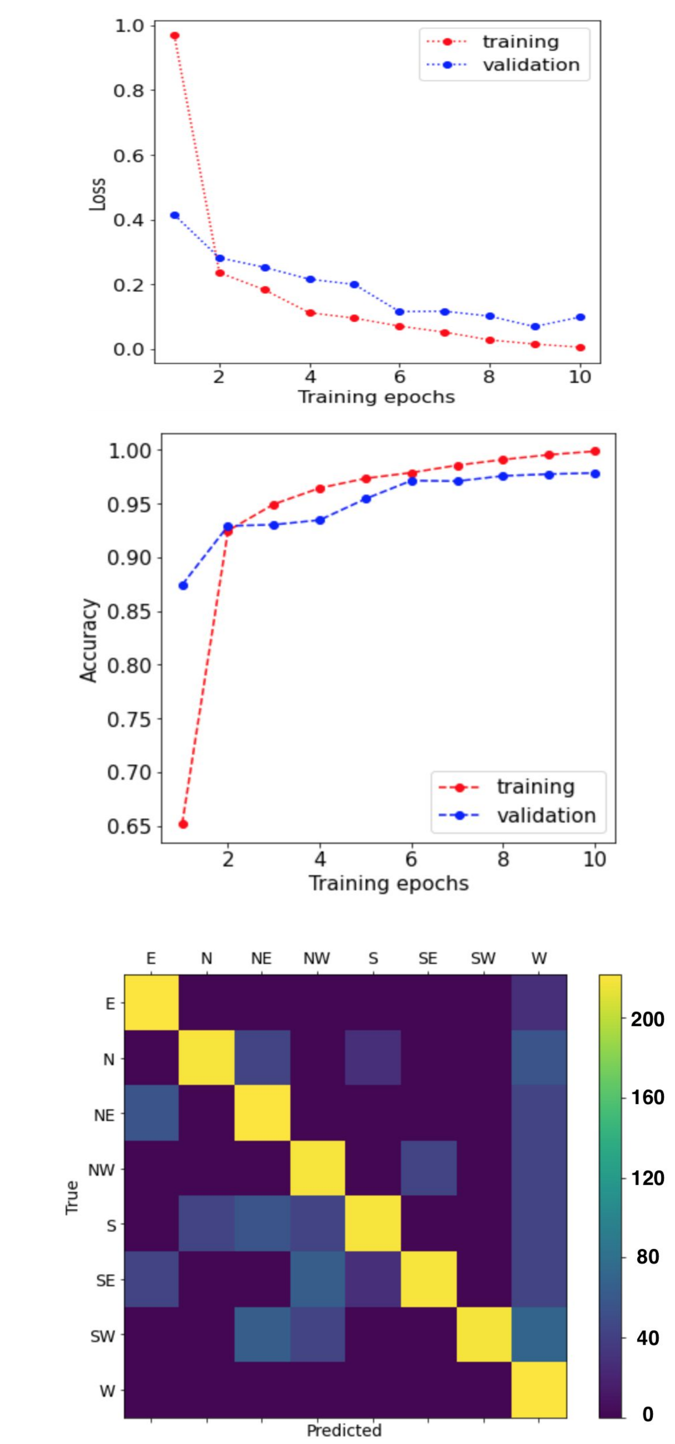
Interpreting our learning curves:
Observing the graphs of both the loss and accuracy of our model, we can see that the validation tends to follow the training statistics as it moves towards a high accuracy and low loss, showing a decent ability of the model to generalize from the training data to the testing dataset.

FORCE-TYPE DETECTION MODEL



Validation Accuracy for Force-Type Detection model:
97.3%

FORCE-DIRECTION DETECTION MODEL



Validation Accuracy for Force-Direction Detection model:
97.8%

7. Discussion

- Handwritten letters and digits can be classified using machine learning models with high accuracy. These models can be used to evaluate students' answers in written exams.
- However, the application of such models needed to be extended beyond the recognition of characters.
- In this work, we developed deep learning models to assist the evaluation of hand drawn (physics based) free body diagrams.
- Our results showed impressive validation accuracies around 97%, demonstrating that they have a decent ability to classify force vectors into their direction and force-type.
- Here we developed the force-direction detection model only based on 8 directions. This model can be further improved to detect the angle (between 0 - 360 degrees) associated with the force vector.
- We expect to develop the models further by integrating force-type and force-direction detection models together to evaluate the hand drawn free body diagrams without manual inspection.

Reference :

1. K. Simonyan et. al., Very Large Convolutional Networks for Large Scale Image Recognition, arxiv: 1409.1556, (2015).
2. Convolution image: https://www.researchgate.net/figure/A-convolutional-neural-networks-CNN_fig6_321286547
3. Pooling and activation image: https://ip.cadence.com/uploads/901/cnn_wp-pdf
4. Neuron image: https://medium.com/@jayeshbahire/the-artificial-neural-networks-handbook-part-4-d2087d1f583e
5. Neural Network image: https://www.astroml.org/book_figures/chapter9/fig_neural_network.html
6. TensorFlow keras tools: https://www.tensorflow.org/api_docs/python/tf/keras

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