Transfer Possibilities of a Deep Learning System from Medicine into Aviation

**Abstract**

Coming originally from neuroscience, the concept of artificial neural networks is getting more attention since a few years thanks to deep learning. As one of the most recent and hyped technologies, deep learning (DL) has by far outperformed classical machine learning approaches. It is being used by many industries in applications like computer vision, natural language processing, and knowledge representation and reasoning. However, applying a novel technology in a real-world environment can be difficult. For this purpose, the medical industry was screened regarding the use of deep learning and how similar use cases can be transferred to the aviation industry. The discoveries include developed frameworks for genomic exon detection that can be used with minor modifications to detect lightning strike damages on aircraft, given the fact that there is enough data to train the damage detection model since deep learning is hungry for data.

**Detexon**

Given the direct link of a genomic mutation within an exon to disease manifestation, it is of fundamental interest to identify exons within a genome for individual drug development. Genome sequence data is therefore fed as nucleoside chains into a convolutional neural network (CNN) that outputs triplets of nucleosides in a fully connected layer. Similar to how polymerase does, a long short-term memory (LSTM) network reads the sequence which then gets into a classifier.

Implementing this classifier into an object detection architecture like YOLO or Mask R-CNN, combined with RoI Align, exons can be detected with unmatched accuracy both in terms of error rate and localization, as seen below in a 4-pixel-chain (AGCT) depiction of a detected exon.

**Swot Analysis: DL**

- **Strengths**
  - Time and Cost effective, low error rate
  - Prediction, Detection, Natural Language, Genetic Algorithms, and more, all within same language
  - Ability to analyze big data
  - Customizable for various tasks
  - Enabling new business models

- **Weaknesses**
  - No expertise (experts are highly expensive right now and have freedom to choose)
  - Understanding the inner computation difficult (as of now)
  - Data hungry

- **Opportunities**
  - Identification of use cases and manual processes (direct savings)
  - Cooperation within an expert group or research institute
  - European and state fundings

- **Threats**
  - Aviation regulations regarding artificial intelligence
  - Error rate not small enough for aviation purposes

**Autoinspect**

Manual inspection of aircrafts for skin damages is a time consuming and exhausting task because of the high concentration needed at any time and weather conditions. Safety regulations dictate an immediate check-up after a reported lightning strike, which is a regularly occurring damage type. The damage images are fed into a convolutional neural network, where the features are extracted (intuitive representation below) when training the model, and then used to classify and detect damages in a real-world test setting, similar to the medical use case of Detexon.

Since there is an already developed model of Detexon up to the stage of TRL 4, which by NASA’s definition is a standalone prototype processing fully representative data sets, investors are easier to approach to proof feasibility of the technology. From a financial point of view, about seven percent could be saved in early technology development (TRL 2 - TRL 4). Considered by itself, this thesis, including the investigation and assessment in the course of it, is to be viewed as a technology transfer instrument, bringing AutoInspect to a conceptual TRL 2, similar to the approach of research days.

**Technology Transfer**

The process of technology transfer describes the knowledge transfer in early technology development and begins right after the detailed description of the observation made (TRL 1) up to a stage where the technology is being developed to market (TRL 9). In the case of Detexon (TRL 4) minor changes have to be made to the model since there is no need for an LSTM. The rest of the model could be used for AutoInspect to be built on top of it. Since for the input images it is important to have color channels (RGB), the feature layers would be more complex than Detexon, but similar to the basic framework of YOLO or R-CNN. Nonetheless, the development difficulty of AutoInspect is expected to drop significantly with a learning curve due to similar work already done.

**Conclusion**

The task of damage detection does not constitute a challenge for state of the art deep learning models. The bottleneck in simply every deep learning case is the data. With deep learning, the manual feature engineering is eliminated, yet its advantages over traditional machine learning approaches can only be demonstrated when having the correct amount of data; and in the general deep learning case more is more. For a highly accurate system which can withstand aviation authority’s safety requirements, of which one is that a new system has to provide an equivalent or higher level of safety, the deep learning system has to be trained well. The damage images gathered in the course of this thesis at the maintenance site in Frankfurt were not of a sufficient quality so that preprocessing would be inevitable. In fact, preprocessing takes up to 90 percent of time for the early development stages. Cost savings would therefore be relativized, with the exception of a learning curve, since the proper functioning of the deep learning model is based on many factors, of which one is data.