Recent advances in Convolutional Neural Networks and open opportunities in eMainteance

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Deep learning is currently at the peak of Gartner Hype Cycle, meaning that there are large expectations from industry stakeholders. These expectations are not unjustified, since digitalization (pervasive sensing) and distributed computing enables leaps which transform the AI paradigm on a biannual basis.

Some important recent leaps are: I) crowdsourcing information from platforms such as the Amazon Mechanical Turk, ii) collection of Large Scale Databases such as ImageNet (2009), iii) introduction of open challenges such as the ImageNet Large-Scale Visual Recognition Challenge (since 2010), since many recent innovations have been achieved by participants in such challenges, iii) successful large-scale networks such as AlexNet (2012), which convinced the scientific community to place a focus on deep learning, iv) larger explainability of Convolutional Neural Networks (2014) and therefore increased acceptance by practitioners, v) distributing training of a network across separate computers allowing to train the deepest networks in weeks or months where it could have potentially taken years, vi) introduction of network architectures which allow efficient training of deeper networks which would otherwise have led to increasing classification errors together with the increase of depth due to the vanishing gradient problem (e.g. Inception Network (2014) or Residual Networks (RestNets) (2016)).

This paper explores how these advances in deep learning open new possibilities for application to maintenance in relation to scarcity of measurements such as: i) the ability to transfer learning between AIs and across disciplines, like the retraining of AlexNet for inspecting bridges ii) using similarity metrics to train certain AIs with just one or few samples of each class (one shot learning), iii) dataset augmentation, iv) automated feature learning as opposed to the traditional feature engineering.

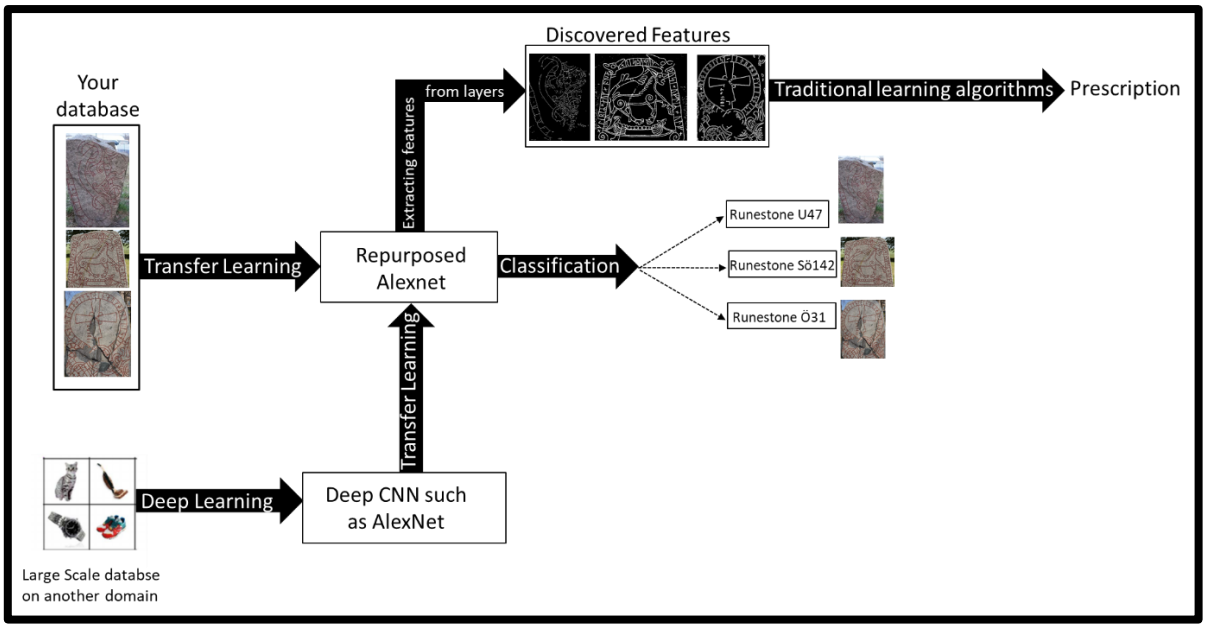

Illustration of discovering features through feature learning and transfer learning