


Chapter 7


Semantic Medical Image Analysis: An Alternative to Cross- Domain Transfer Learning

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ABSTRACT

The recent advancement in imaging technology, together with the hierarchical feature representation capability of deep learning models, has led to the popularization of deep learning models. Thus, research tends towards the use of deep neural networks as against the hand-crafted machine learning algorithms for solving computational problems involving medical images analysis. This limitation has led to the use of features extracted from non-medical data for training models for medical image analysis, considered optimal for practical implementation in clinical setting because medical images contain semantic contents that are different from that of natural images. Therefore, there is need for an alternative to cross-domain feature-learning. Hence, this chapter discusses the possible ways of harnessing domain-specific features which have semantic contents for development of deep learning models.

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INTRODUCTION

Semantic Medical Image Analysis (SMIA) might be the “next big thing” in scientific computing (SC) within the context of the healthcare industry basically because its analytics is contingent on semantics in its entirety (i.e. Intention, Meaning, and Context (IMC)). In SMIA resources such as processes, data, tools, document, device, people will be attended to. In the context of Semantic Computing (SC), SMIA is scoped around analytics, integration, description languages for semantics, and interfaces, etc. Additionally, applications that include biomedical systems, SDN, IoT, wearable computing, cloud computing, context awareness, mobile computing, big data, search engines, question answering, multimedia, and services will draw on SC in the 21st century to influence SMIA. The presentation in Table 1 shows what these applications will contribute to (or draw on) SC and aggregate impact on SMIA, which Machine Learning (ML) will benefit from. The sign (í) show that IMC cannot be applied nor relevant, while (ü) shows it can be applied or relevant.

Table 1. Application and their contribution to SC and aggregate impact on SMIA

| Application Type | Contribution To SC | Use SC | Applied to Introduce | | |
|--------------------|--|--|----------------------|---------|---------|
| | | | intention | meaning | context |
| Biomedical systems | Make data available | Provide semantic wherewithal To support or implement semantic Retrieval | × | ✓ | × |
| IoT | Make data available from disparate sources | Solve interoperability problem | × | ✓ | ✓ |
| SDN | Provide room for semantic failover | To cater for collective intelligence | ✓ | × | ✓ |
| Context Awareness | Provide the context for SC to derive its meaning | To Make context explicit | ✓ | ✓ | ✓ |
| Wearable Computing | Provide user context's Information | To ensure contexts are interoperable | ✓ | ✓ | ✓ |
| Cloud Computing | Makes computing Resources available | Helps to achieve portability & interoperability | ✓ | ✓ | ✓ |
| Big Data | Provide Deep learning Resources & make sense of data | Support meaningful data analytics | ✓ | ✓ | ✓ |
| Multimedia | Help retrieval of content | To use context to reach varied audience | × | × | ✓ |
| Question Answering | Provide underlying Framework for SC | Provide deep semantic parsing to get the right response across | × | ✓ | ✓ |

*SMIA (Semantic Medical Image Analysis); SC (Semantic Computing)

SMIA rely on Machine Learning Algorithms (MLA) to build implementable models using sample data. These sample data are “training data,” which provide the knowledge to train a model or algorithm to have its own information (i.e. experience) to predict outcomes accurately. This happens after training a model without necessarily programming it explicitly to perform the predictive task (Zhang, 2020). Where SC comes in is in the area of understandable insight and applicable intelligence. As such, SC

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