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Ph.D. Mid-Term Evaluation

Design and Evaluation of Parallel and Scalable Machine Learning Applications in Biomedical Modelling Applications

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Motivation

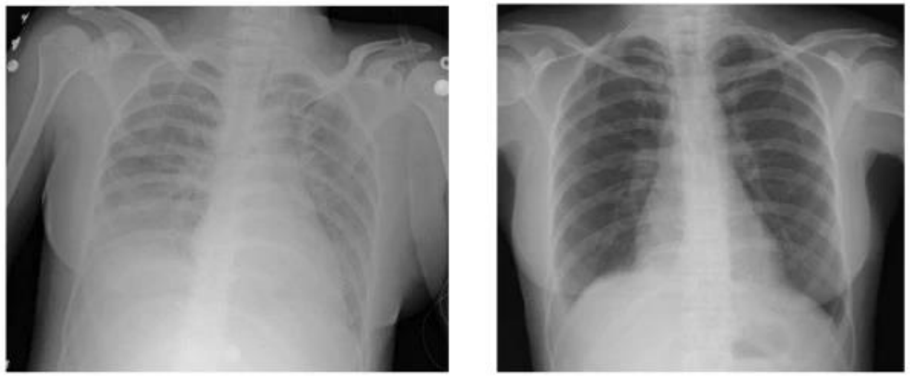
Acute Respiratory Distress Syndrome

- Acute Respiratory Distress Syndrome (ARDS) is a severe condition that affects a significant fraction of Intensive Care Unit (ICU) patients with a high mortality rate [1].
- It is characterised by bronchoalveolar injury and alveolar collapse, and is visible in chest X-rays as bilateral infiltrates in the lungs.
- Early detection is generally associated with positive outcomes [4,5].
- Diagnosis based on the "Berlin Definition" [6].

I. Direct injury
1. Aspiration.
2. Diffuse pulmonary infection (e.g., bacterial, viral, *Pneumocystis*.
3. Infection, and others).
4. Near-drowning.
5. Toxic inhalation.
6. Lung contusion.

II. Indirect Injury
1. Sepsis syndrome, with or without clinically significant hypotension, (e.g., systolic blood pressure ⩽ 90 mm Hg), with or without evidence of infection outside the lung. This syndrome can be described as having both signs of systemic inflammation (i.e., by abnormalities of body temperature, heart rate, respiratory rate, and white blood cell count) and signs of organ system dysfunction including, but not limited to, pulmonary, hepatic, renal, central nervous, and cardiovascular systems.
2. Severe nonthoracic trauma as indicated by:
   (1) Clinical description.
   (2) Scoring systems such as the Injury Severity Score (ISS) or APACHE II/III.
   (3) Treatment interventions such as the Treatment Intervention Scoring System (TISS).
3. Hypertransfusion for emergency resuscitation.
4. Cardiopulmonary bypass (rare).

ARDS Risk Factors [2]



Comparison of ARDS (left) and healthy lungs (right) [3]

Machine Learning in Medical Applications

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- Machine Learning (ML) is well established as a tool in the medical field.
- Lundervold & Lundervold compile the work being done in applications of ML to analyse medical images [7].
- Das *et al*. and Wang *et al*. both describe developing simulation models for the cardiovascular and respiratory systems [8,9].
- Huddar *et al*. and Meyer *et al*. discuss prediction over clinical data using ML models with varying complexity [10,11].

Table 2
A short list of deep learning applications per *organ*, *task*, *reference* and *description*.

Brain		
Brain extraction	[269]	A 3D CNN for skull stripping
Functional connectomes	[270]	Transfer learning approach to enhance deep neural network classification of brain functional connectomes
	[271]	Multisite diagnostic classification of schizophrenia using discriminant deep learning with functional connectivity MRI
Structural connectomes	[272]	A convolutional neural network-based approach (https://github.com/MIC-DKFZ/TractSeg) that directly segments tracts in the field of fiber orientation distribution function (fODF) peaks without using tractography, image registration or parcellation. Tested on 105 subjects from the Human Connectome Project
Brain age	[273]	Chronological age prediction from raw brain T1-MRI data, also testing the heritability of brain-predicted age using a sample of 62 monozygotic and dizygotic twins
Alzheimer's disease	[274]	Landmark-based deep multi-instance learning evaluated on 1526 subjects from three public datasets (ADNI-1, ADNI-2, MIRIAD)
	[275]	Identify different stages of AD
	[276]	Multimodal and multiscale deep neural networks for the early diagnosis of AD using structural MR and FDG-PET images
Vascular lesions	[277]	Evaluation of a deep learning approach for the segmentation of brain tissues and white matter hyperintensities of presumed vascular origin in MRI
Identification of MRI contrast	[278]	Using deep learning algorithms to automatically identify the brain MRI contrast, with implications for managing large databases
Meningioma	[279]	Fully automated detection and segmentation of meningiomas using deep learning on routine multiparametric MRI
Glioma	[280]	Glioblas [illegible]
	[281]	Deep lea [illegible] sting
	[282]	Automat [illegible] work
	[283]	AdaptAl [illegible] oblastomas (BRATS [illegible]
Multiple sclerosis	[284]	Deep lea [illegible] uish between multiple [illegible]
Kidney		
Abdominal organs	[285]	CNNs to [illegible] en, and stomach in T_2-we [illegible]
Cyst segmentation	[266]	An artifi [illegible] kidneys
Renal transplant	[286]	A deep-l [illegible] uish between [illegible] ected [illegible]
Prostate		
Cancer (PCa)	[illegible]	[illegible] nage) nested [illegible] ierarchical [illegible] oefficient, 5-fold [illegible]
	[illegible]	[illegible] patients with a [illegible] tate biopsy with [illegible] withou [illegible]
	[289]	[illegible] tomat [illegible] s tissues with multipar [illegible]
	[290]	Deep CN [illegible] n and the bag-of-w [illegible] distinguish patholog [illegible] or prostate benign h [illegible] IR images
	[291]	Designe [illegible] e lesions based on deep [illegible] ADC and T_2-w images r [illegible] arametric MRI. Evaluate [illegible]
	[292]	Designe [illegible] PCa lesions and 450 iden [illegible] ould greatly affect the [illegible] (1) Given limited training data, how can these be augmented in sufficient numbers and variety for fine-tuning deep CNN networks for PCa diagnosis? (2) How can multimodal mp-MRI information be effectively combined in CNNs? (3) What is the impact of different CNN architectures on the accuracy of PCa diagnosis?
Spine		
Vertebrae labeling	[293]	Designed a CNN for detection and labeling of vertebrae in MR images with clinical annotations as training data
Intervertebral disc localization	[268]	3D multi-scale fully connected CNNs with random modality voxel dropout learning for intervertebral disc localization and segmentation from multi-modality MR images
Disc-level labeling, spinal stenosis grading	[294]	CNN model denoted DeepSPINE, having a U-Net architecture combined with a spine-curve fitting method for automated lumbar vertebral segmentation, disc-level designation, and spinal stenosis grading with a natural language processing scheme
Lumbal neural forminal stenosis (LNFS)	[295]	Addressed the challenge of automated pathogenesis-based diagnosis, simultaneously localizing and grading multiple spinal structures (neural foramina, vertebrae, intervertebral discs) for diagnosing LNFS and discover pathogenic factors. Proposed a deep multiscale multitask learning network integrating a multiscale multi-output learning and a multitask regression learning into a fully convolutional network where (i) a DMML-Net merges semantic representations to reinforce the salience of numerous target organs (ii) a DMML-Net extends multiscale convolutional layers as multiple output layers to boost the scale-invariance for various organs, and (iii) a DMML-Net joins the multitask regression module and the multitask loss module to combine the mutual benefit between tasks
Spondylitis vs tuberculosis	[296]	CNN model for differentiating between tuberculous and pyogenic spondylitis in MR images. Compared their CNN performance with that of three skilled radiologists using spine MRIs from 80 patients
Metastasis	[290]	A multi-resolution approach for spinal metastasis detection using deep Siamese neural networks comprising three identical subnetworks for multi-resolution analysis and detection. Detection performance was evaluated on a set of 26 cases using a free-response receiver operating characteristic analysis (observer is free to mark and rate as many suspicious regions as are considered clinically reportable)

Applications in:
- Brain
- Kidney
- Prostate
- Spine

(among others)

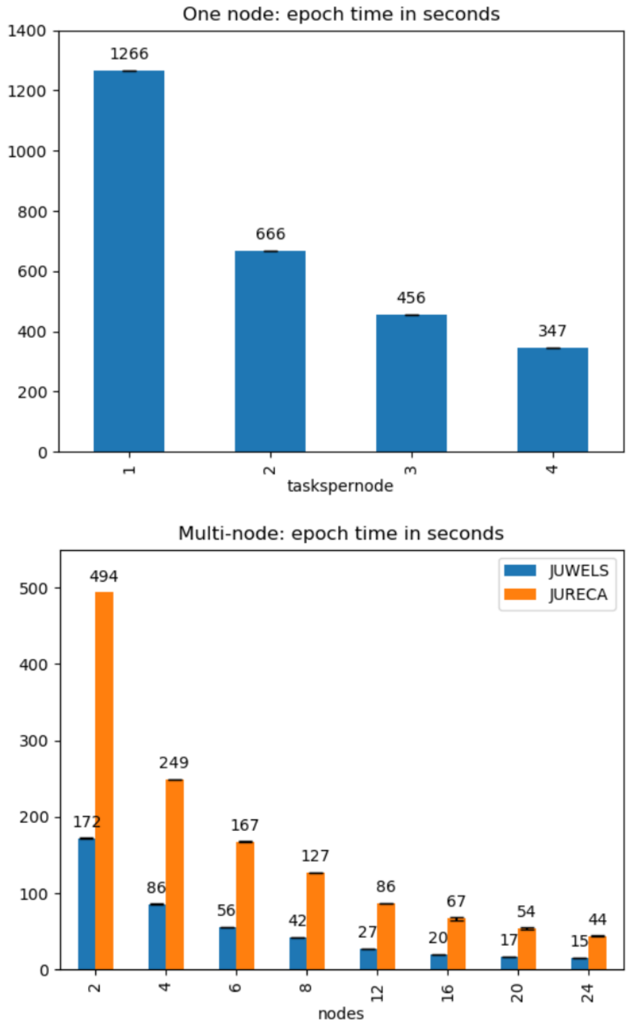
Some ML applications in Healthcare [7]

High-Performance Computing and Machine Learning

- ML can benefit from the Scale-up and Speed-up achieved through HPC.
- Götz *et al.* and Wang *et al.* present parallel implementations of DBSCAN, a well-established clustering algorithm [12,13].
- Erlingsson *et al.* and Sedona *et al.* both discuss HPC-facilitated ML for Remote Sensing applications (Support Vector Machines and Deep Learning, respectively) [14,15]

NODELIST	NODES	PARTITION	STATE	CPUS
dp-cn01	1	dp-cn	reserved	48
dp-dam01	1	dp-dam	idle	96
ml-gpu01	1	ml-gpu	allocated	16

Sample node Information on DEEP



Speed-up and scale-up values for training a multispectral model [15]

Smart Medical Information Technology for Healthcare

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- The SMITH project is one of the four consortia of the German Medical Informatics Initiative (MII) [16].
- Aims to establish infrastructure for research in healthcare:
  - Define governance architecture for this infrastructure.
  - Determine paths of communication and data sharing between partner university clinics and research centres.
- Two clinical use cases:
  - HELP – Hospital-wide electronic medical record-based computerized decision support system to improve outcomes of patients with blood-stream infections.
  - ASIC – Algorithmic Surveillance of ICU Patients.

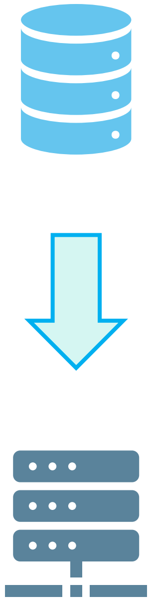
SMITH
Smart Medical Information Technology for Healthcare

Problem Statements and Suggested Solutions

ARDS as a Major Use Case

- ARDS – major application field in the ASIC use case.
- Challenge 1: Disease onset, progression, diagnosis, and treatment need algorithmic support.
    - Berlin Definition aids diagnosis [6].
    - No consensus on optimal treatment strategy [1,17,18,19].
    - Wealth of clinical data, but analysis is slow.
- Challenge 2: Medical staff lack the necessary knowledge in HPC to conduct simulations.
- Opportunity: Use of ML and HPC to speed up analysis.
    - Nottingham Physiology Simulator/Warwick Physiological Model obtained through project partners [19,20].
    - HPC resources within the Jülich Supercomputing Centre.

SMITH
Smart Medical Information Technology for Healthcare



JÜLICH Forschungszentrum
JÜLICH SUPERCOMPUTING CENTRE

Parallel Research Opportunity

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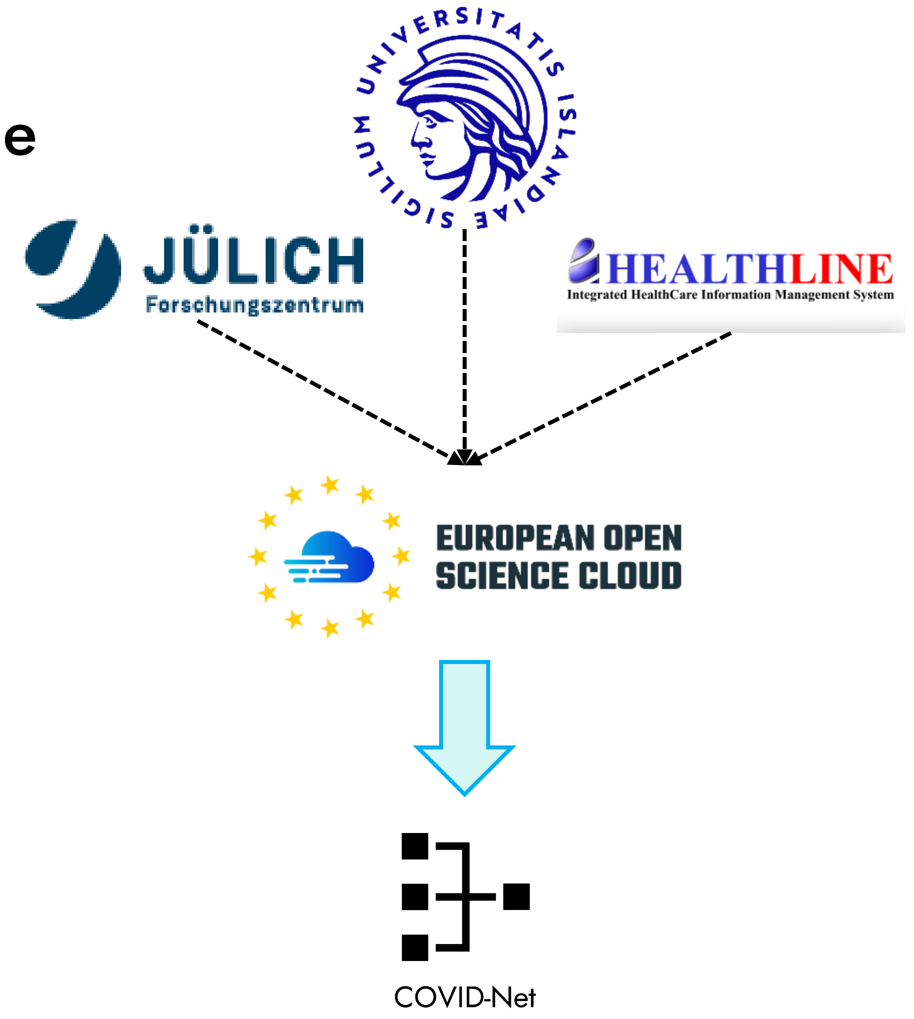
- Covid-19: wealth of data and research made available within a short time:
  - Similar application field to ARDS.
  - Joining established knowledge in the field with experience gained from working in SMITH.
- EOSC Fast-Track Grant (FZ-Jülich/HÍ/e-HealthLine).
- Co-supervising M.Sc. Thesis Gísli Ingólfsson:
  - Verifying outputs of Deep Learning model for chest X-ray classification [21].
  - Testing the model "as is" on new data.
  - Transfer Learning in real-world applications.

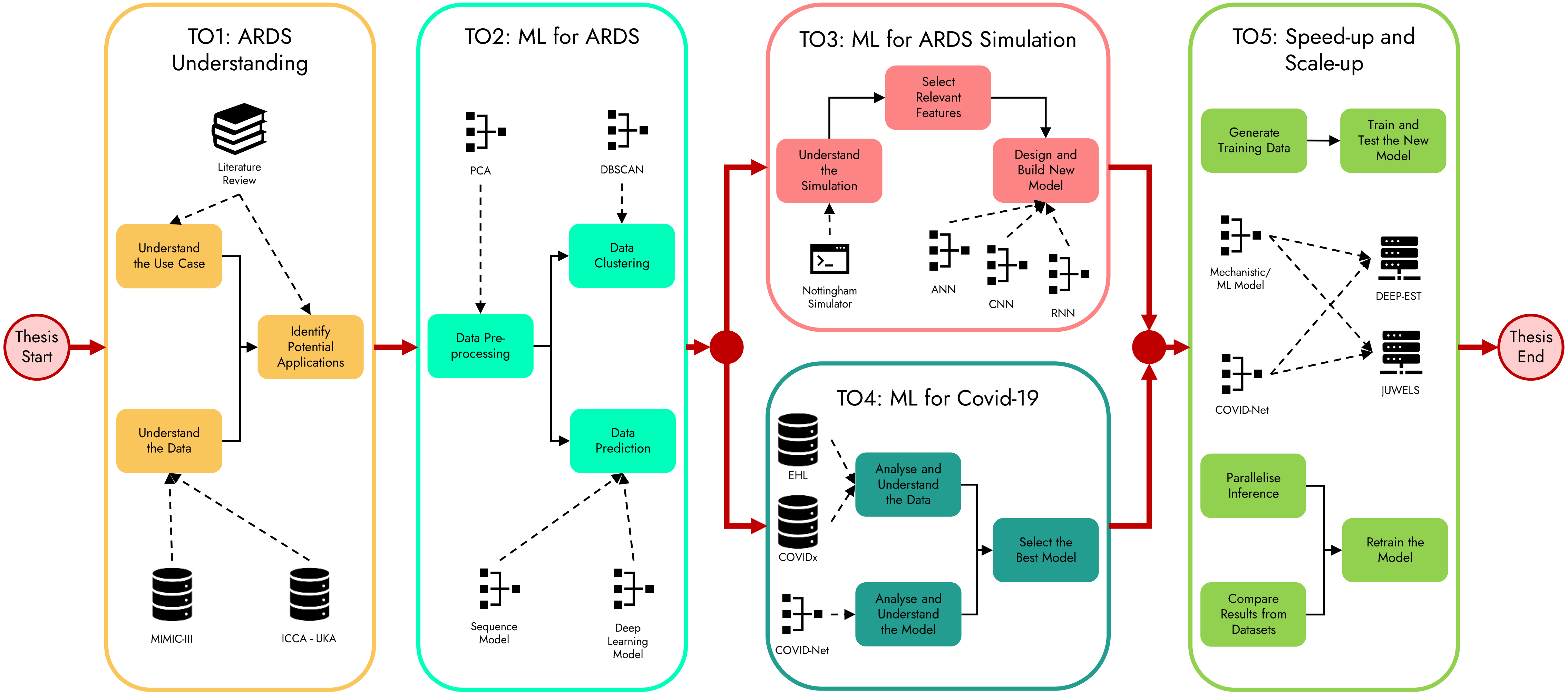


Thesis Objectives

Thesis Objectives

- TO1 – Understanding the disease model of ARDS: Markers, Diagnosis, Treatment.
- TO2 – Exploring machine learning models for application in ARDS: timeseries prediction, deep learning.
- TO3 – Exploring mechanistic modelling for ARDS patient simulation.
- TO4 – Exploring machine learning models for Covid-19 chest X-ray image analysis.
- TO5 – Speed-up and Scale-up of mechanistic and machine learning models using HPC resources.

Thesis Outline



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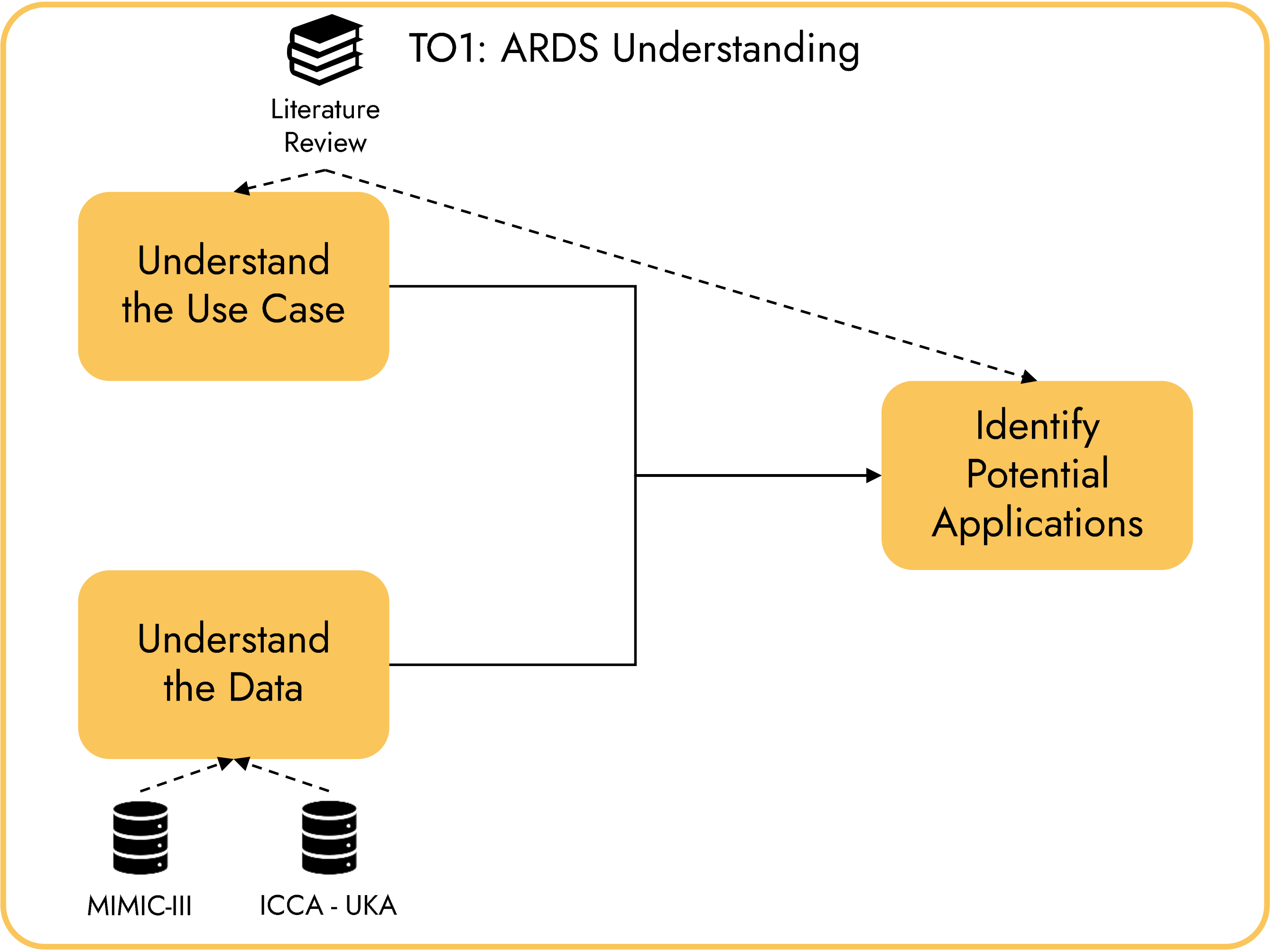

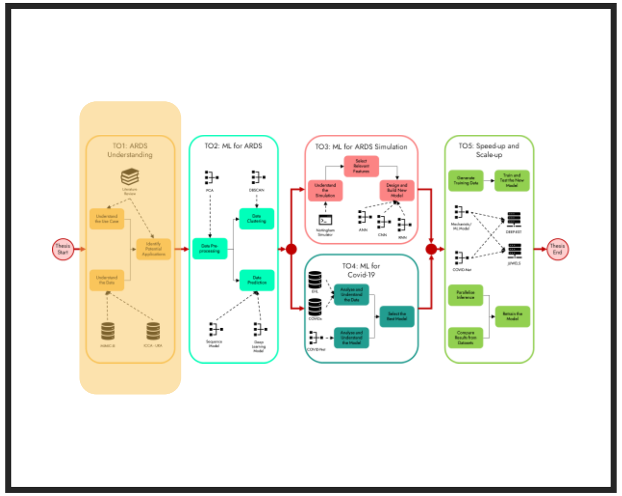

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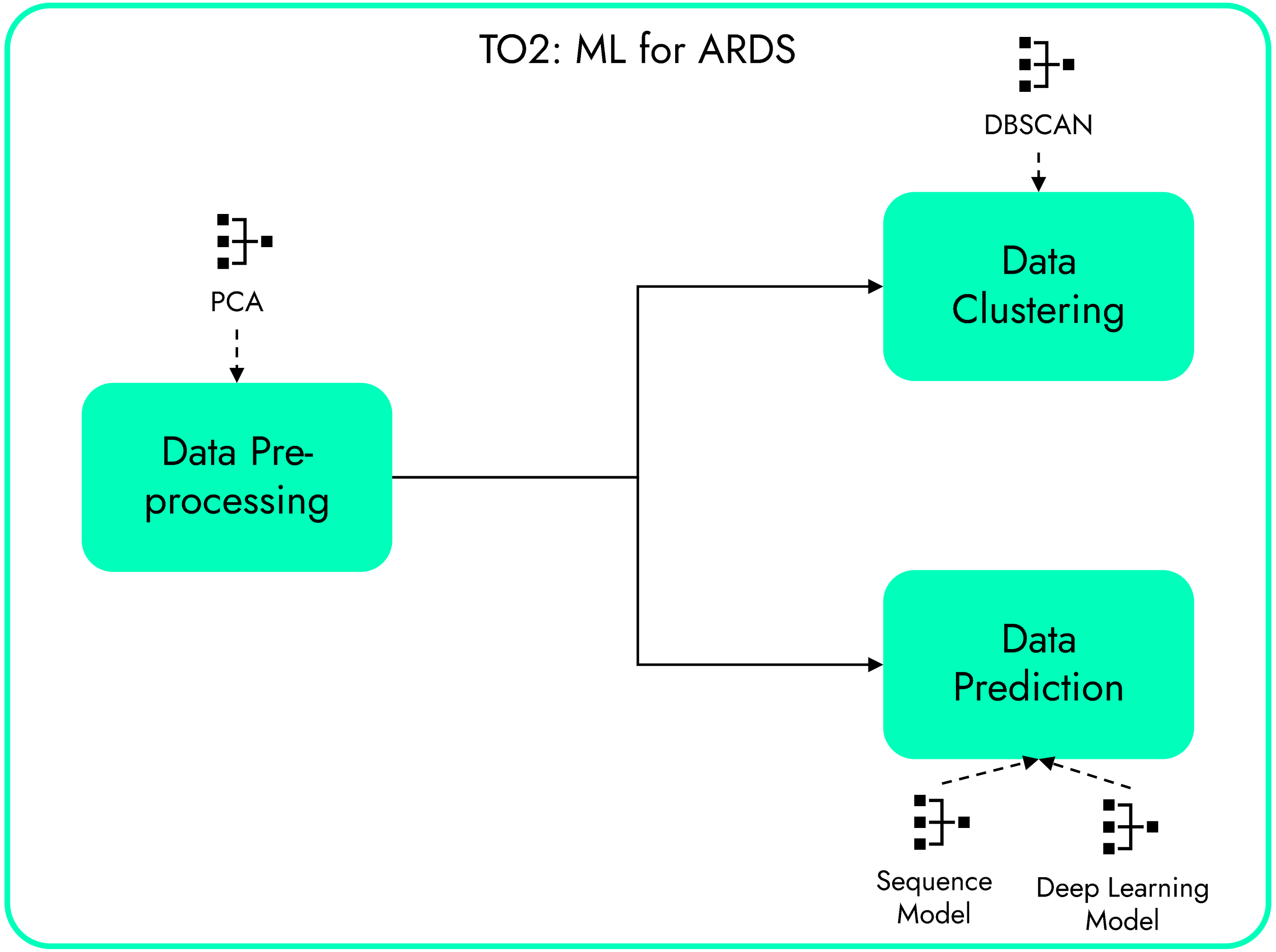

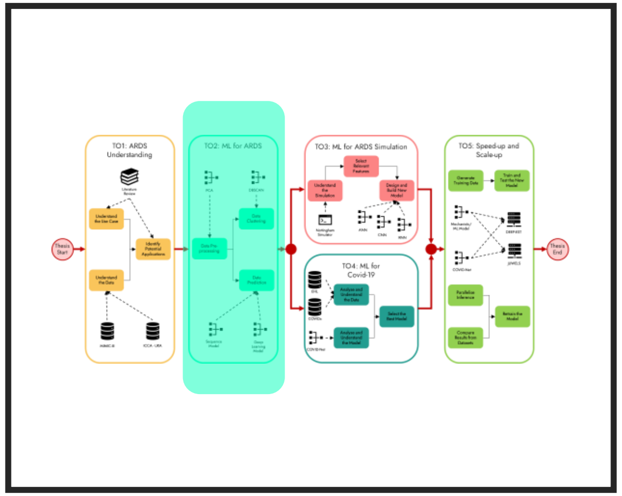

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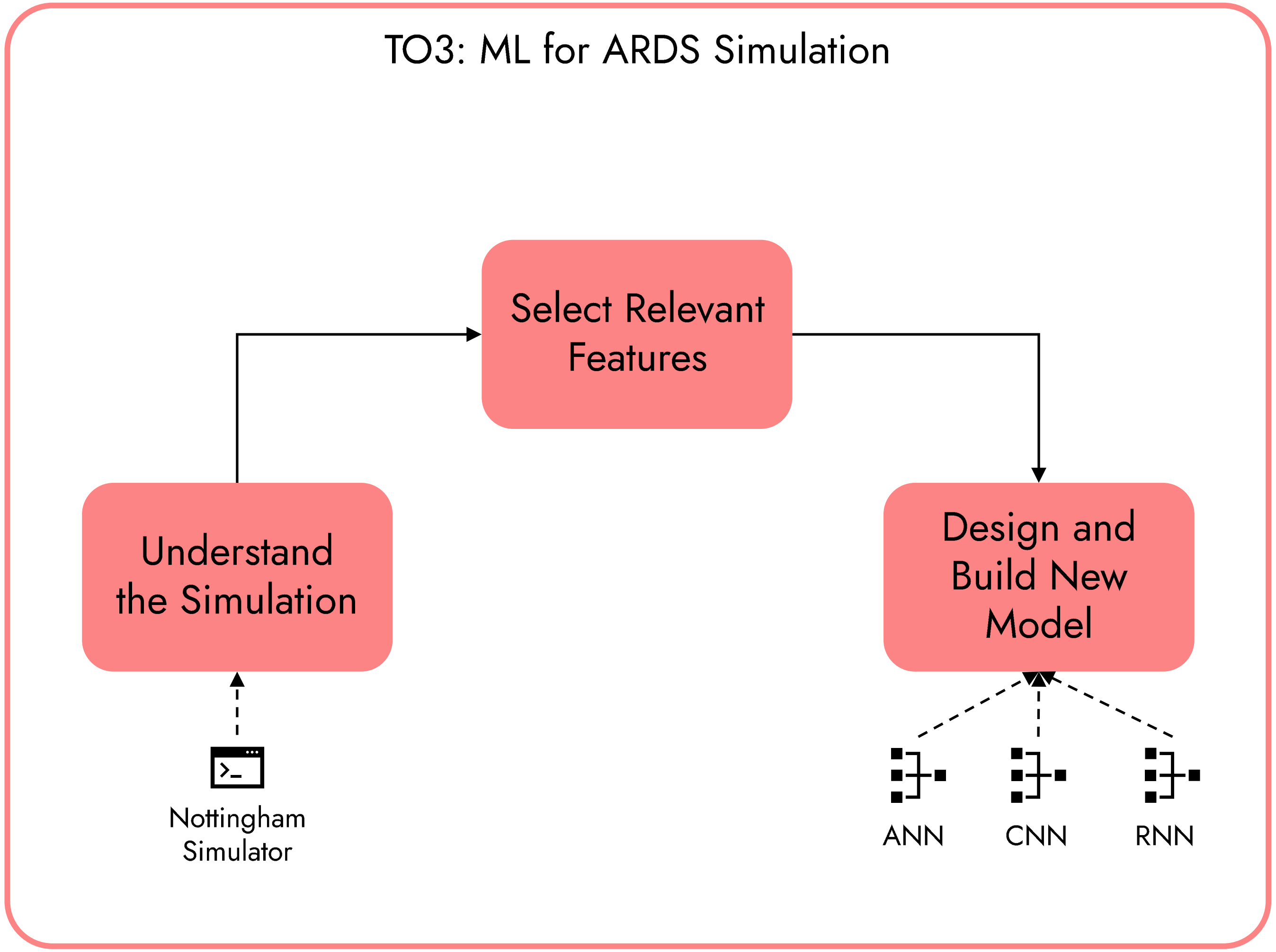

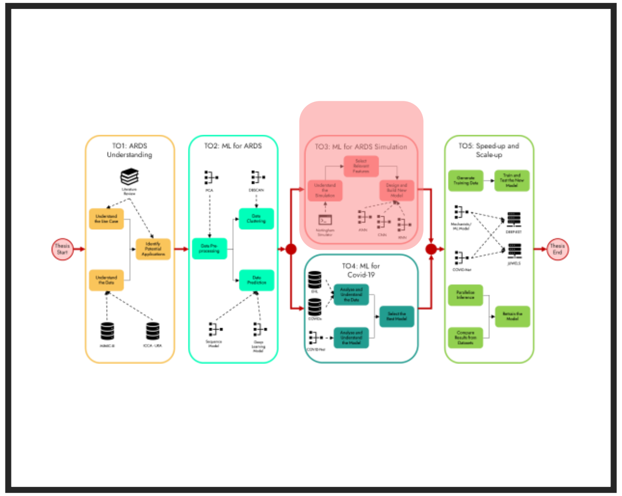

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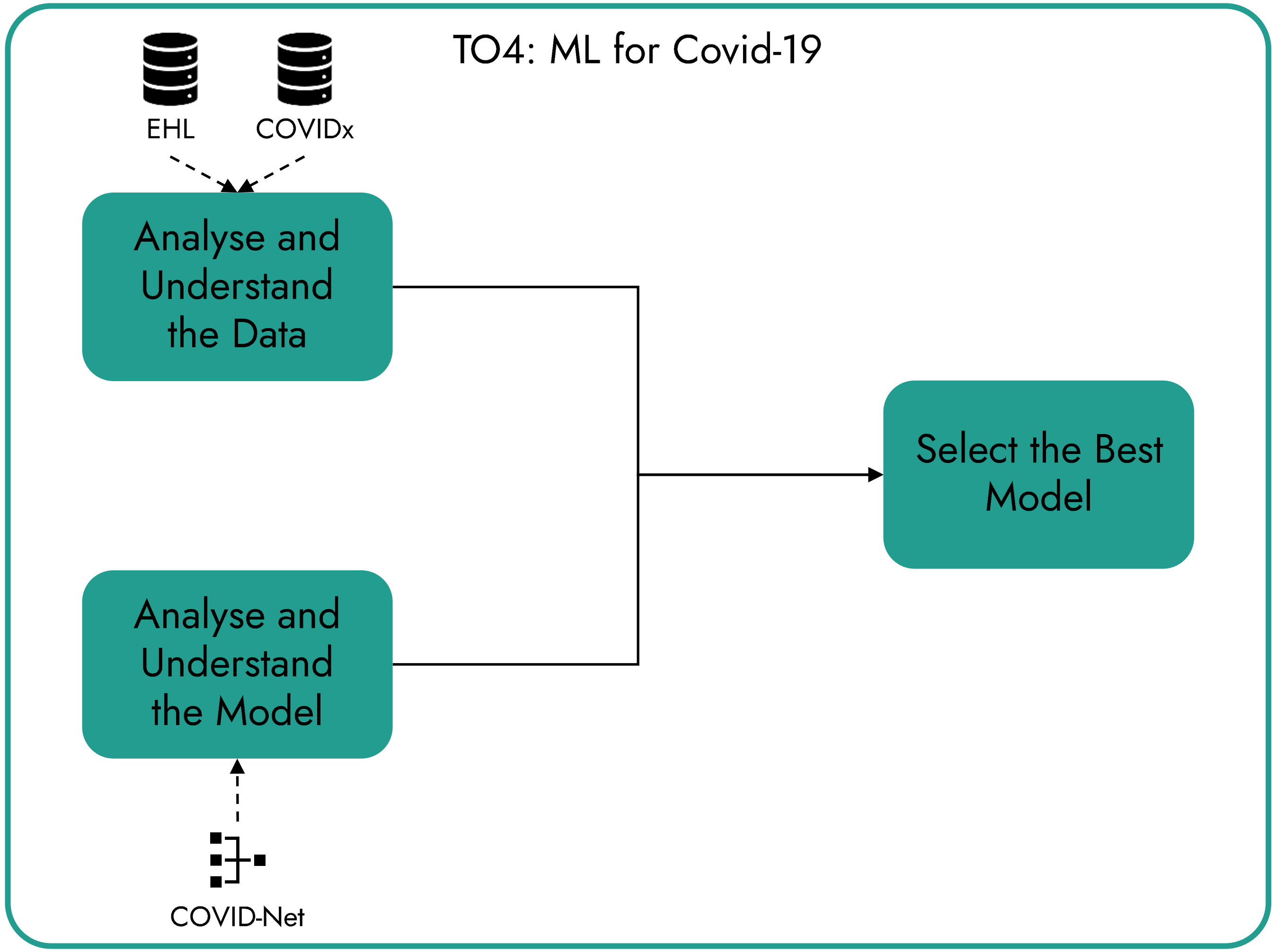

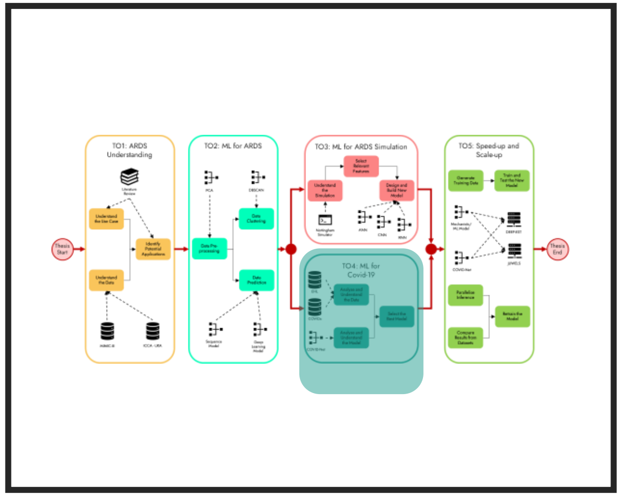

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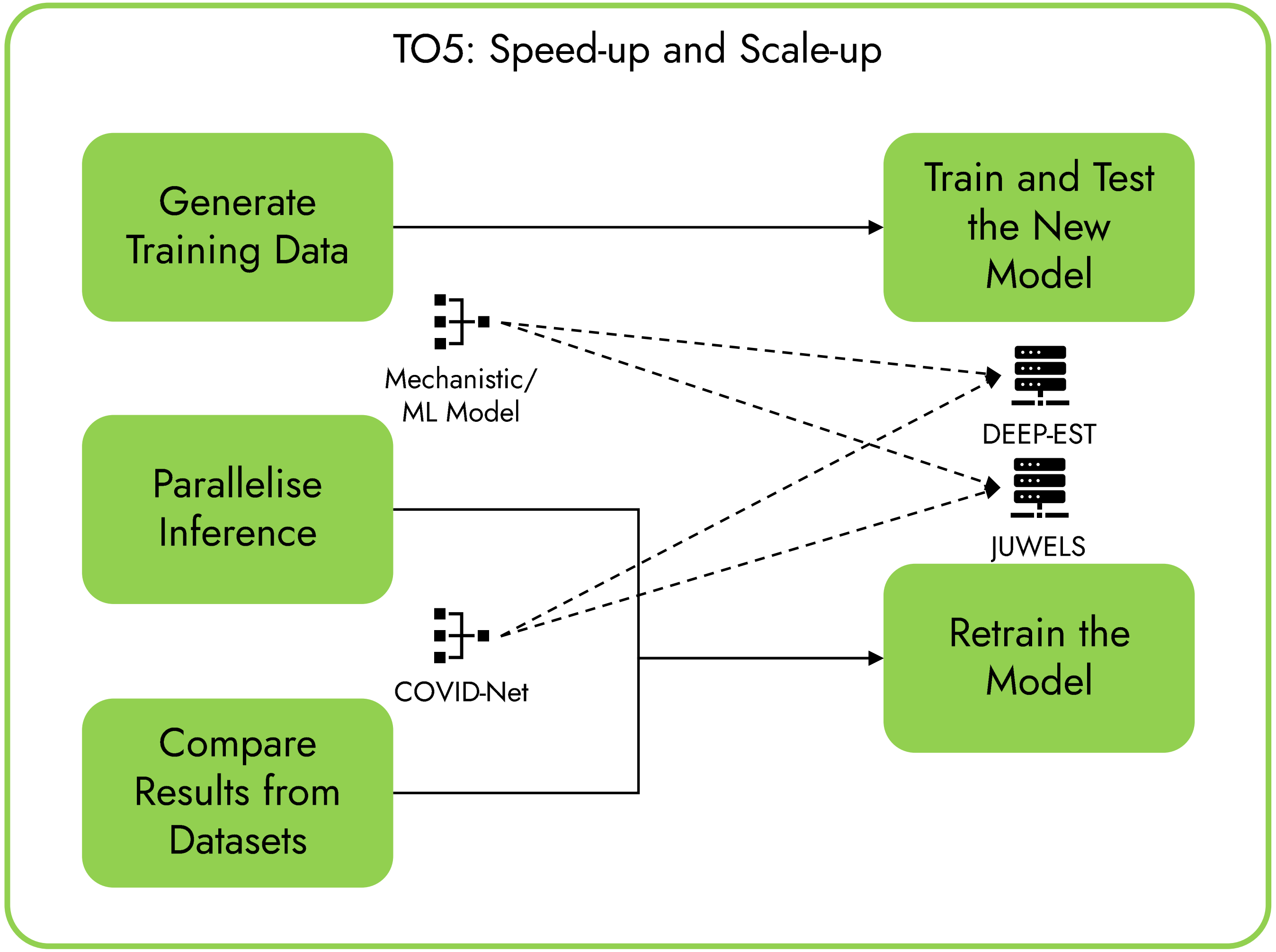

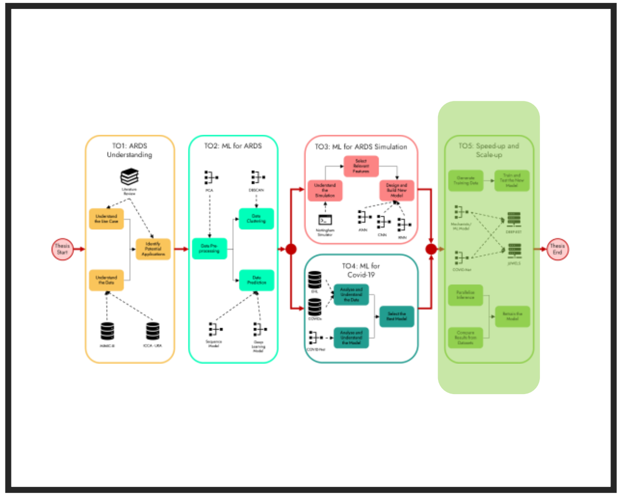

System Blueprint – ML for Healthcare

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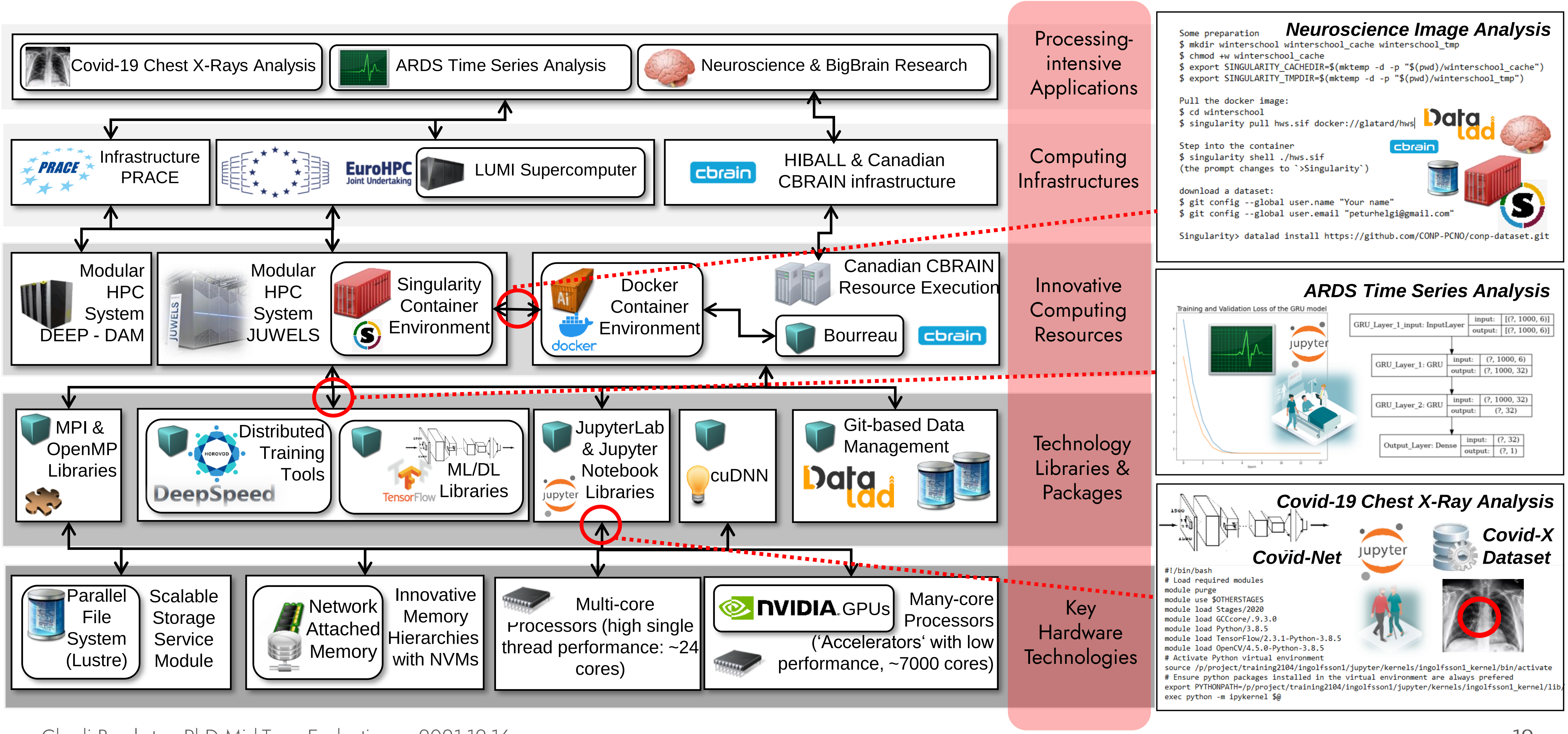
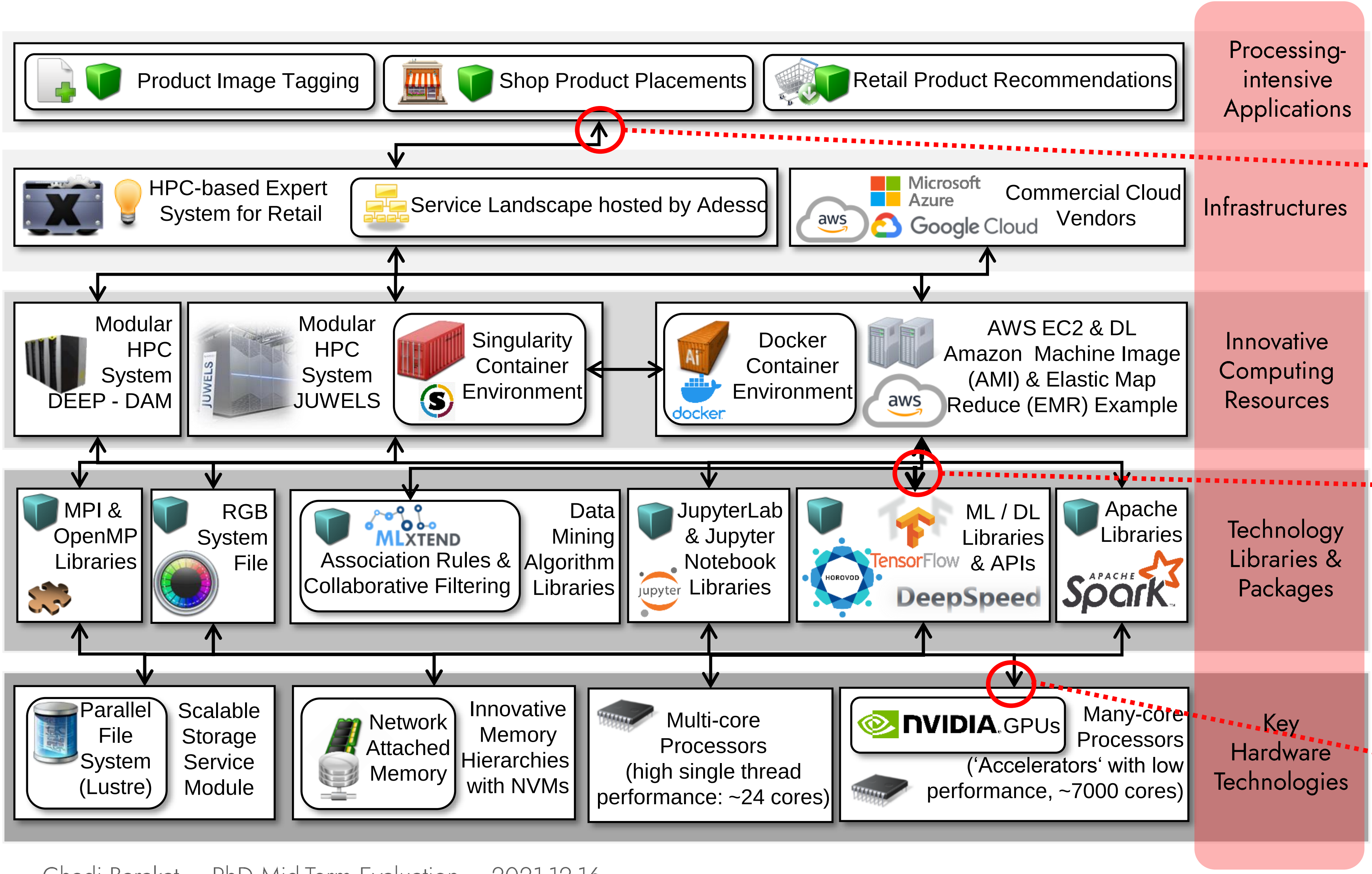


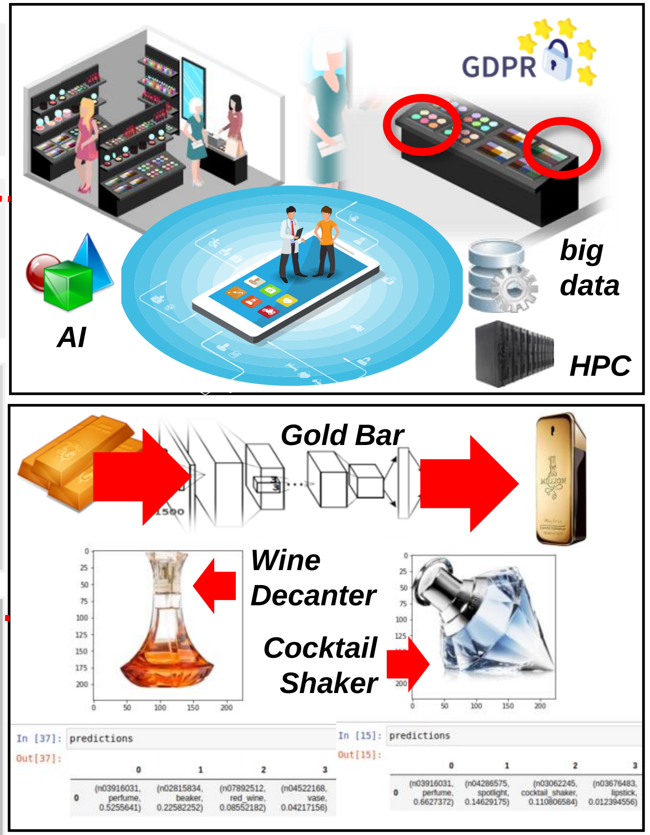
Mid-Term Status

- Started – July 2019
- Courses
  - Deep Learning (10 Credits)
  - Cloud Computing and Big Data (6 Credits)
  - Text Analysis and Rhetoric for PhD Students (5 Credits)
- Reading Course
  - Machine Learning Transfer Applications
  - On4Off Project involvement + Publication (not counting to Thesis)

- Expected end – End 2022
- Publications: Medical infrastructure work, Retail Infrastructure work
- Planned Publications: Covid-19 work, Simulator

System Blueprint – ML for Retail





#GPUs	images/s	speedup	Performance per GPU [images/s]
1	55	1.0	55
4	178	3.2	44.5
8	357	6.5	44.63
16	689	12.5	43.06
32	1230	22.4	38.44
64	2276	41.4	35.56
128	5562	101.1	43.45

#128 GPUs in parallel

Thank you for your attention

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