

IESTI01 – TinyML

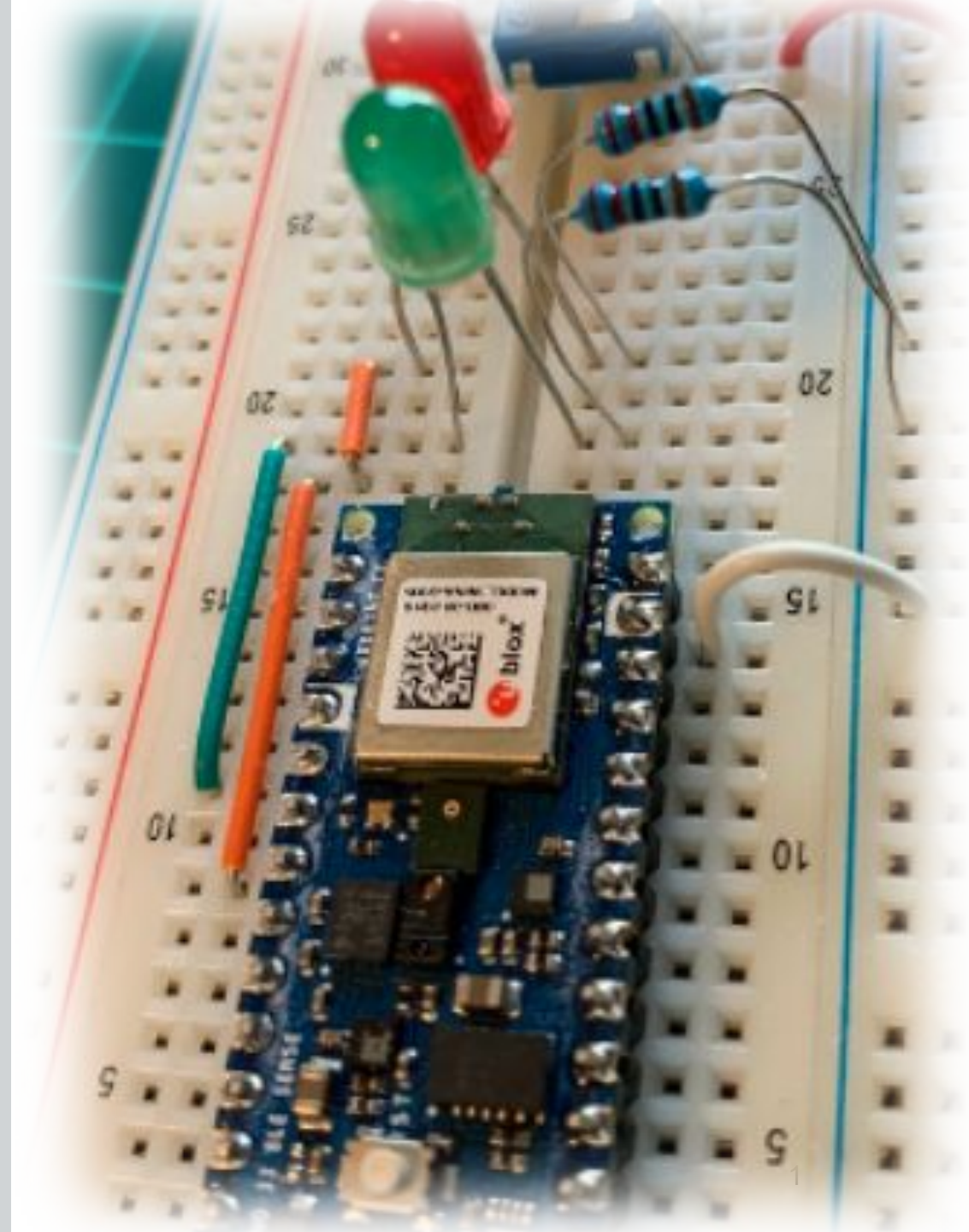
Embedded Machine Learning

15. ML Applications Overview AI Lifecycle and ML Workflow



Prof. Marcelo Rovai

UNIFEI



TinyML Application

Examples (Classification)

Predictive Maintenance



Motion, current, audio and camera

- **Industrial**
- White goods
- Infrastructure
- Automotive

Asset Tracking & Monitoring



Motion, temp, humidity, position, audio and camera

- Logistics
- Infrastructure
- Buildings
- Agriculture

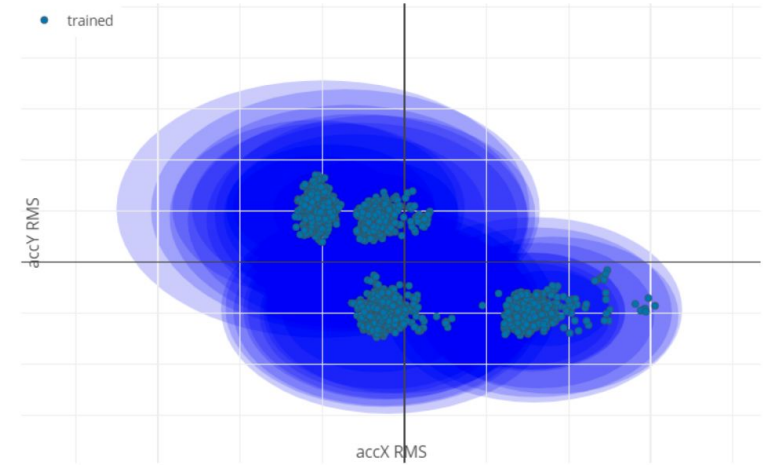
Human & Animal Sensing



Motion, radar, audio, PPG, ECG

- Health
- Consumer
- Industrial

Industrial – Anomaly Detection



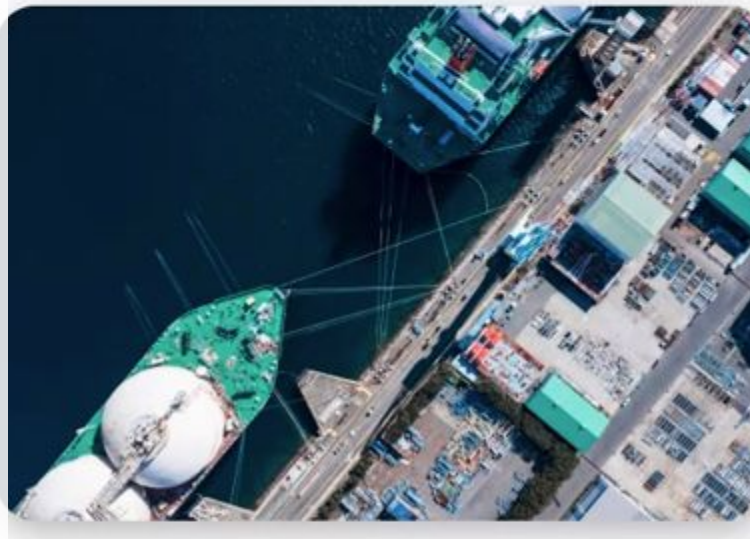
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- **Agriculture**



Human & Animal Sensing



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Agriculture - Cow Monitoring

Using the Internet of Things for Agricultural Monitoring

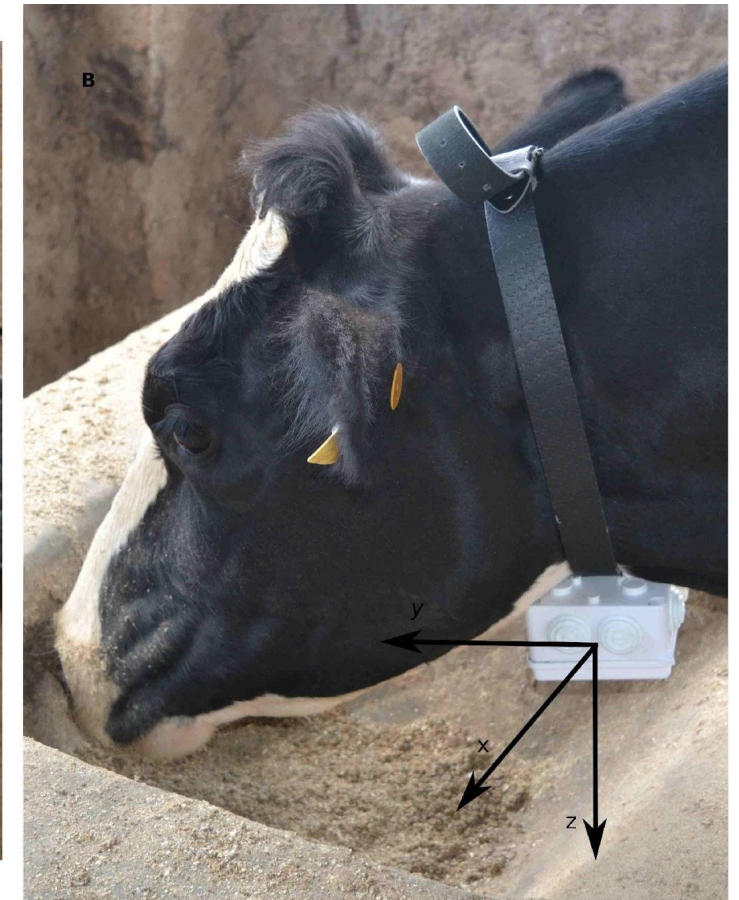
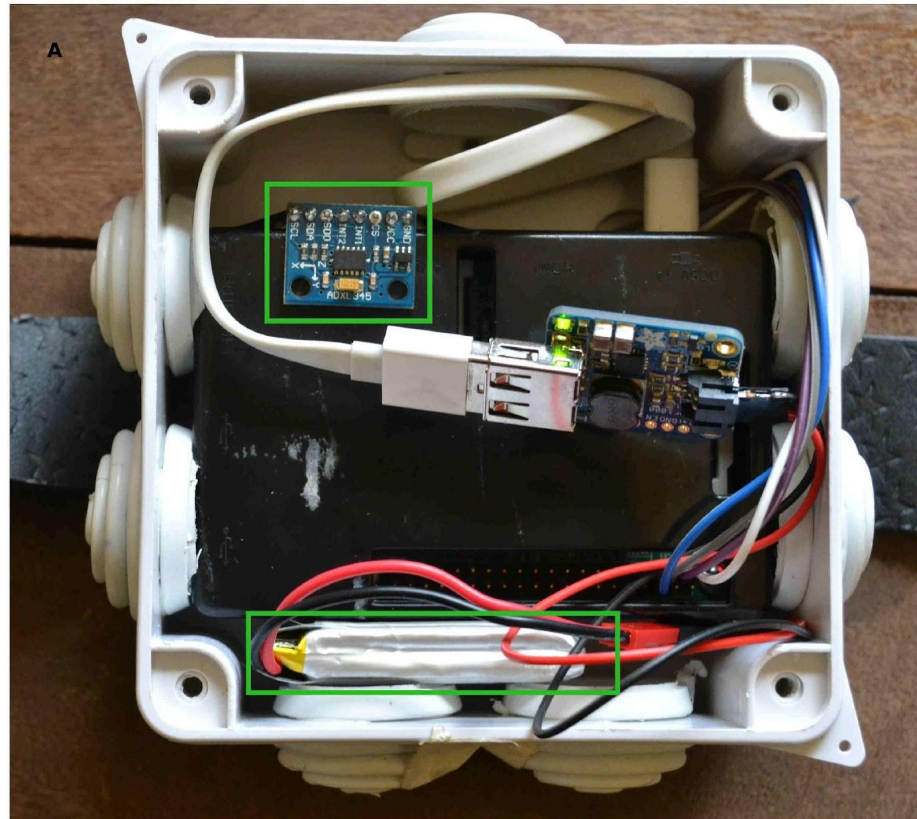
“We aim to deploy a variety of sensors for agricultural monitoring. One of the projects involves using **accelerometer sensors** to monitor activity levels in dairy cows with a view to determining when the cows are on heat or when they are sick.”



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Kenia



<https://sites.google.com/site/cwamainadekut/research>

Predictive Maintenance



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Human & Animal Sensing



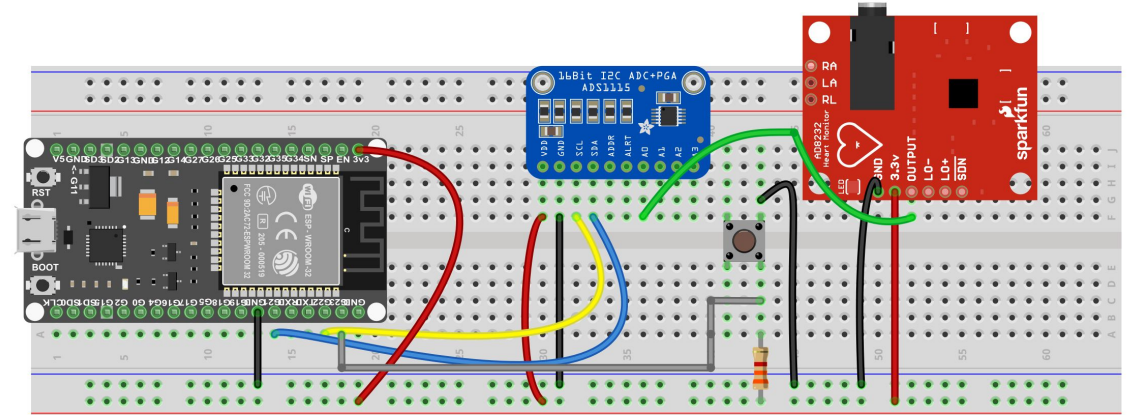
Motion, radar, audio, PPG, ECG

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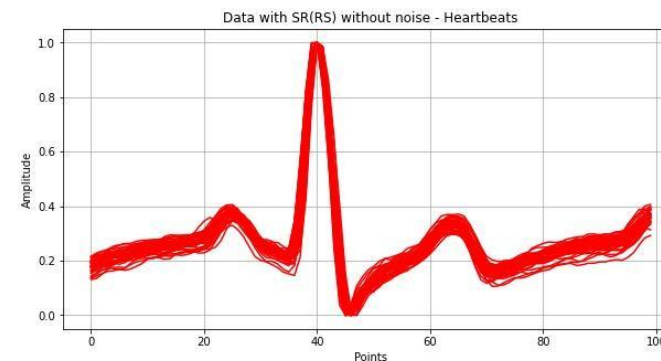
Health - Human Sensing



[Atrial Fibrillation Detection on ECG using TinyML](#)
Silva et al. UNIFEI 2021



fritzing



Guilherme Silva
Engenheiro - UNIFEI

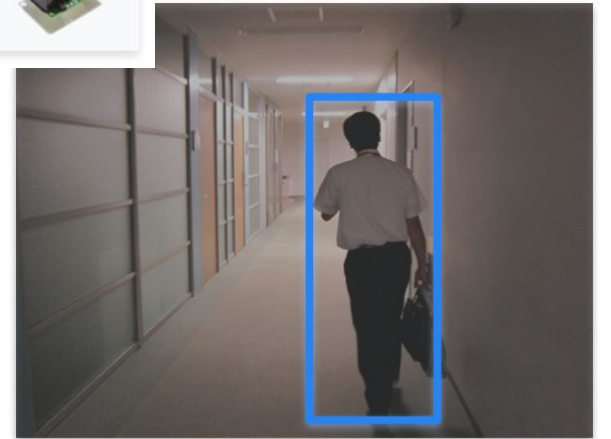
Sound



Vibration



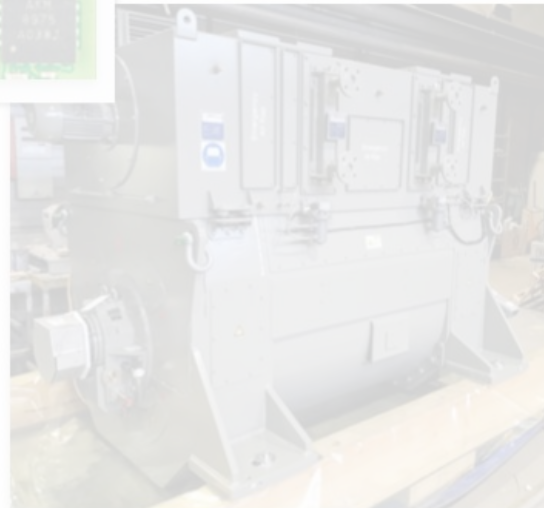
Vision



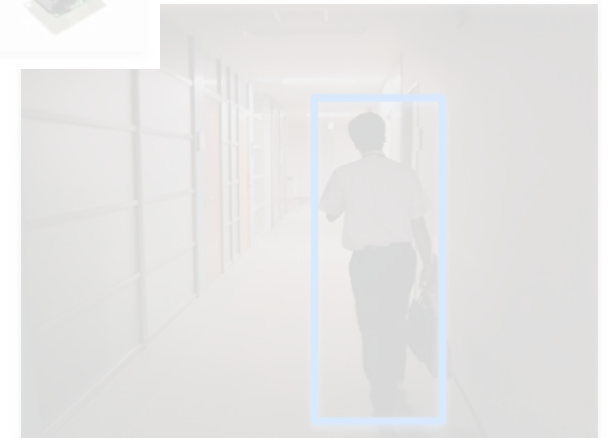
Sound



Vibration



Vision





Classifying mosquito wingbeat sound using TinyML

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Universidade Federal de Itajubá
Itajubá, Brazil
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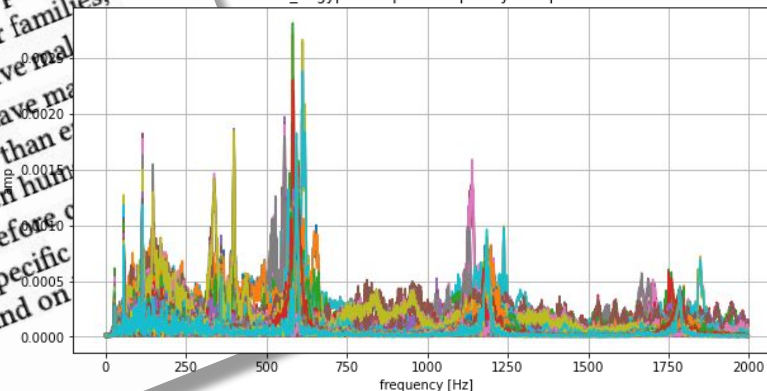
Moez Altayeb
University of Khartoum, Sudan
ICTP, Trieste, Italy
mohedahmed@hotmail.com

ABSTRACT

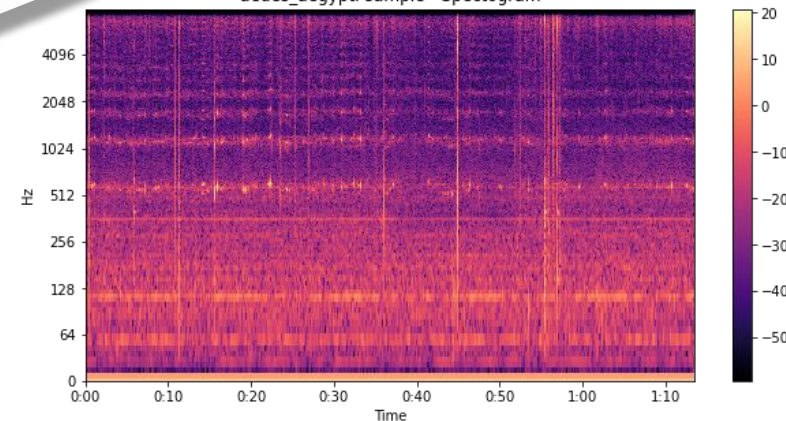
Every year more than one billion people are infected and more than one million people die from vector-borne diseases including malaria, dengue, zika and chikungunya. Mosquitoes are the best known disease vector and are geographically spread worldwide. It is important to raise awareness of mosquito proliferation by monitoring their incidence, especially in poor regions. Acoustic detection of mosquitoes has been studied for long and ML can be used to automatically identify mosquito species by their wingbeat. We present a prototype solution based on an openly available dataset, on the Edge Impulse platform and on three commercially-available TinyML devices. The proposed solution is low-power, low-cost and can run without human intervention in resource-constrained areas. This insect monitoring system can reach a global scale.

affected. People from poor communities with little access to health care and clean water sources are also at risk. Although anti-malarial drugs exist, there's currently no malaria vaccine. Vector-borne diseases also exacerbate poverty. Illness prevents people from working and supporting themselves and their families, impeding economic development. Countries with intensive malaria have much lower income levels than those that don't have malaria. Countries affected by malaria turn to control rather than eradication. Vector control means decreasing contact between human disease carriers on an area-by-area basis. It is therefore possible to be able to detect the presence of mosquitoes in a specific paper presents an approach based on TinyML and on embedded devices.

aedes_aegypti sample - Frequency Components

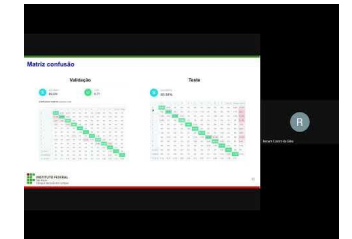
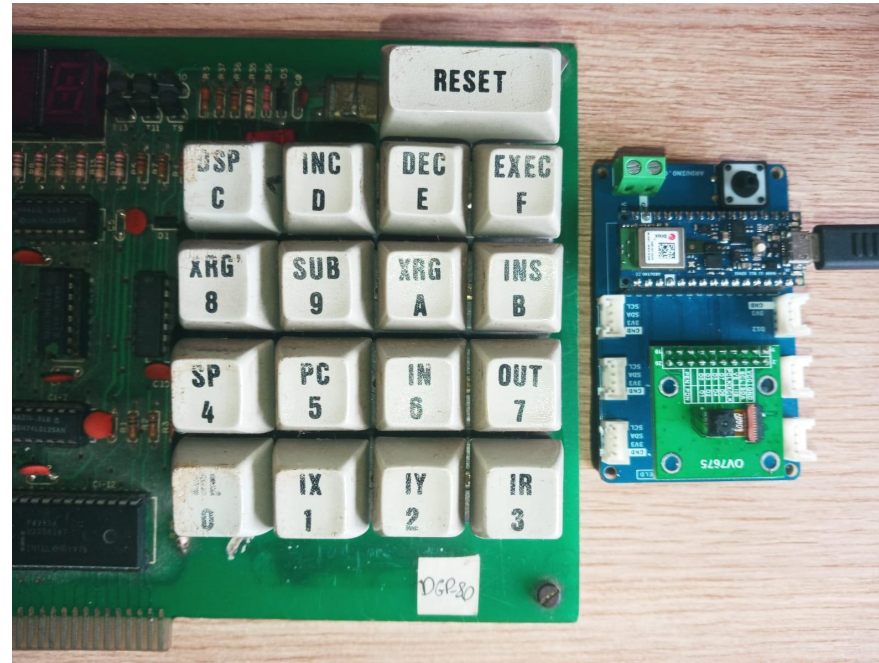
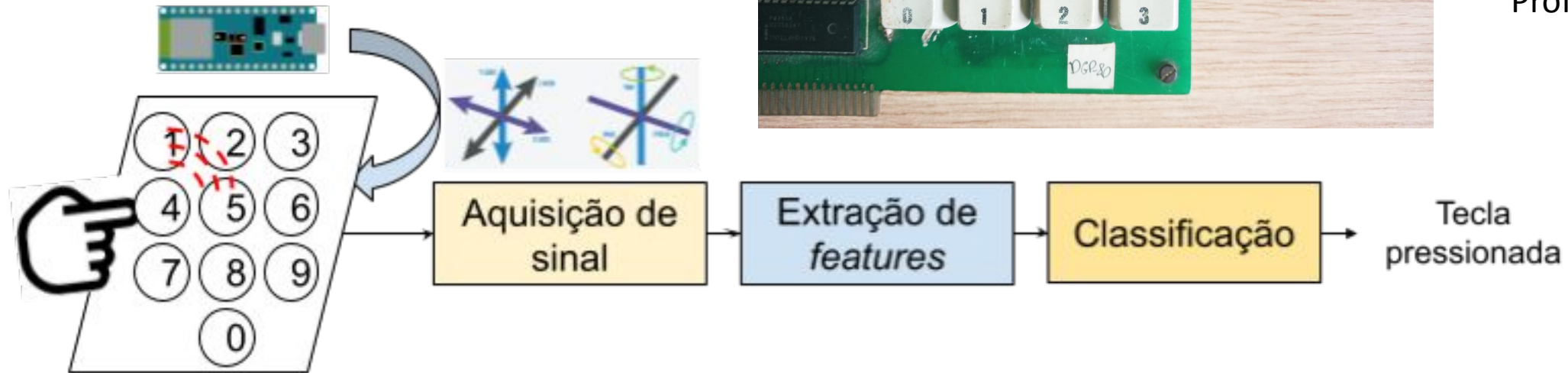


aedes_aegypti sample - Spectrogram



<https://github.com/Mjrovai/wingbeat-mosquito-tinyml>

Key Stroke Detection



Renam Castro
Professor IFESP

Sound



Vibration



Vision



Predict and classify common Elephant behavior



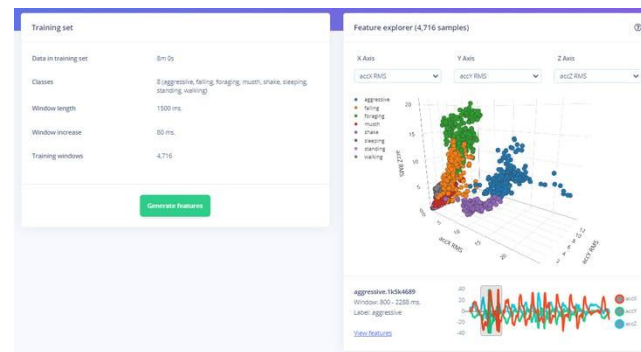
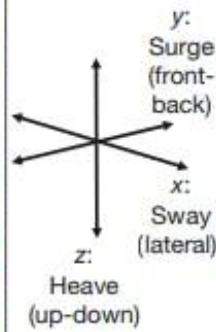
Aggressive



Standing

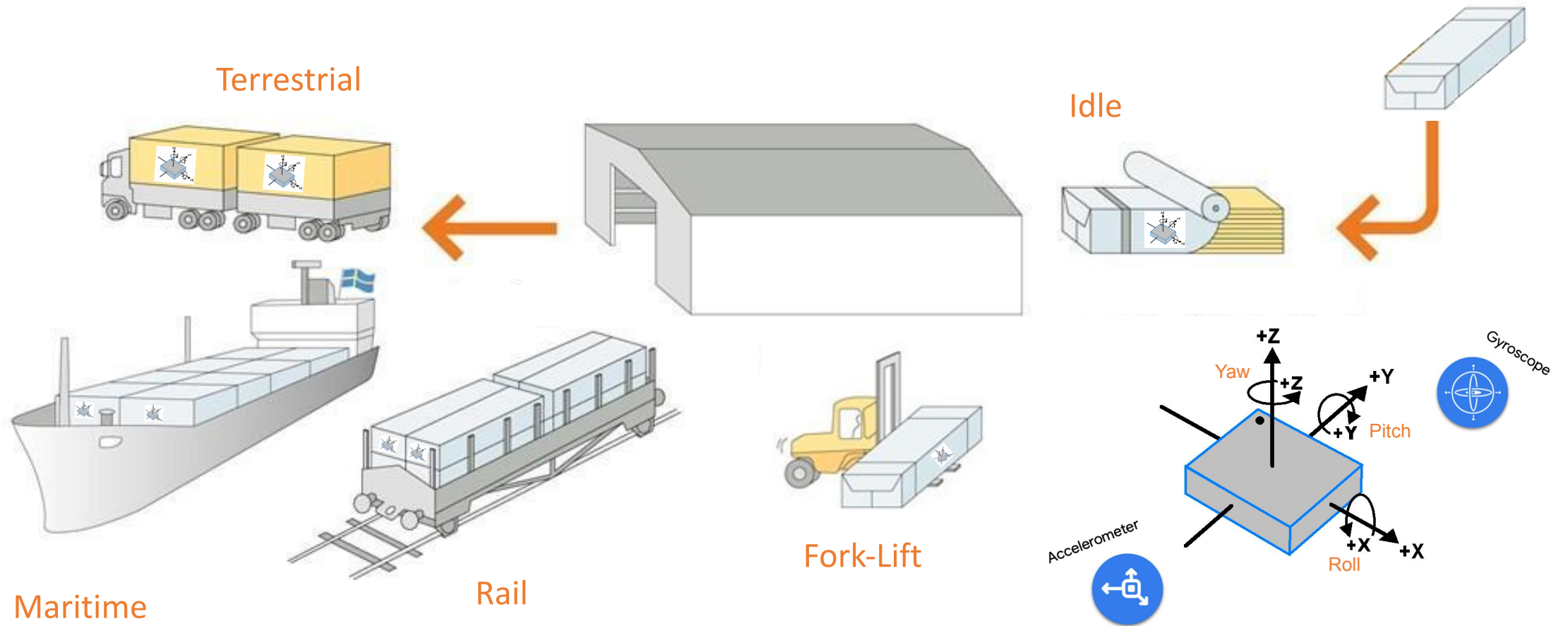


Sleeping



https://www.hackster.io/dhruvsheth_/eletect-tinyml-and-iot-based-smart-wildlife-tracker-c03e5a

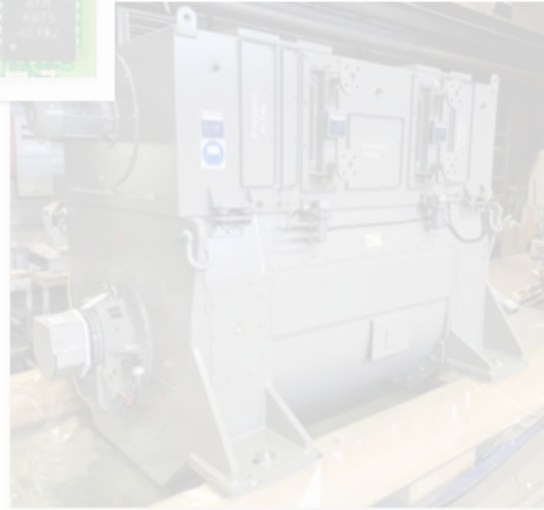
Mechanical Stresses in Transport



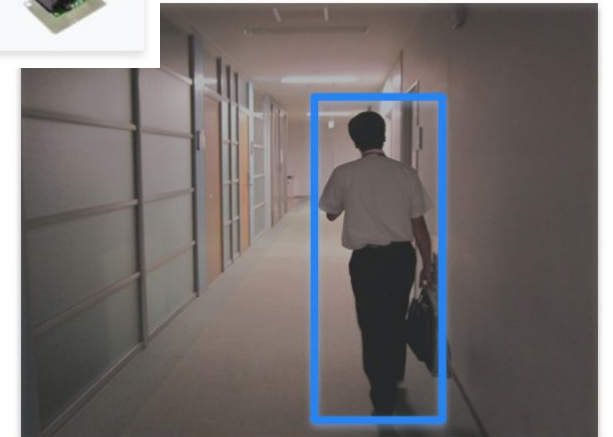
Sound



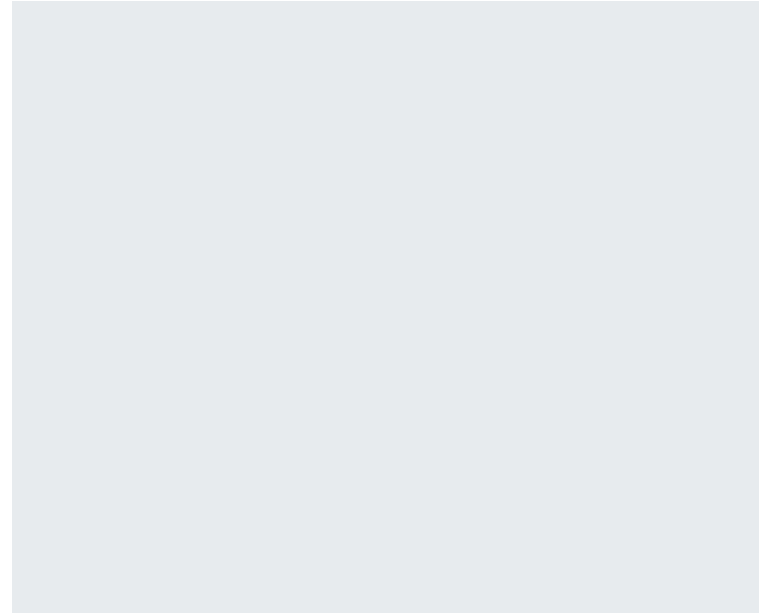
Vibration



Vision



Person Detection



Forest Fire Detection



[TinyML Aerial Forest Fire Detection](#)



[IESTI01 - Forest Fire Detection – Proof of Concept](#)

Coffee Disease Classification



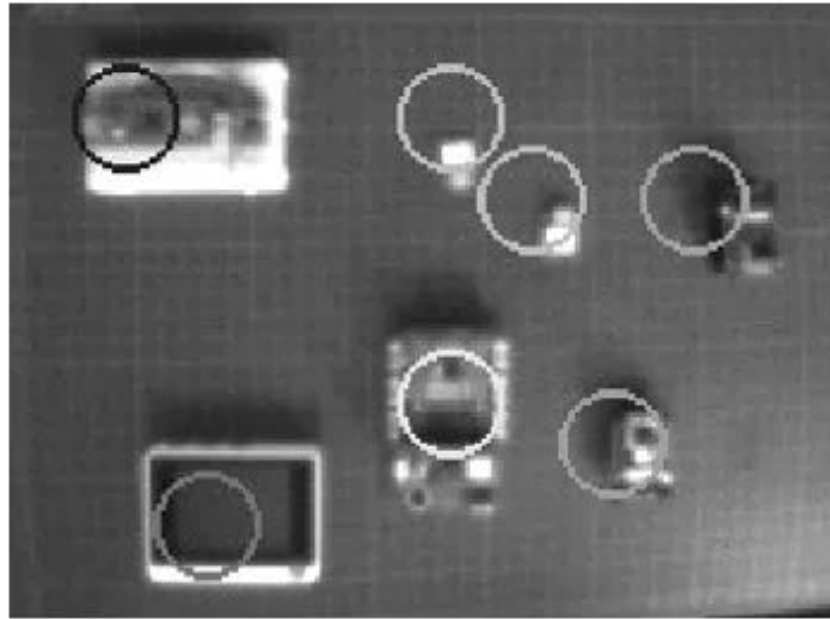
<https://www.hackster.io/Yukio/coffee-disease-classification-with-ml-b0a3fc>



João Vitor Yukio Bordin Yamashita

Graduando em Engenharia Eletrônica pela UNIFEI

Detecting Objects using TinyML (FOMO)



```
***** espcam *****  
x 70    y 150  
x 130   y 170  
***** nano *****  
x 70    y 110  
***** pico *****  
x 150   y 30  
***** wio *****  
x 50    y 50  
***** xiao *****  
x 150   y 110  
x 130   y 130  
6.97512 fps
```

EdgeAI made simple - Exploring Image Processing (Object Detection) on microcontrollers with Arduino Portenta, Edge Impulse FOMO, and OpenMV

Other TinyML / MCUs Project Examples

Vision

- Image Classification with ESP32-CAM
- Image Classification with Portenta H7

[\[Doc\]](#)

[\[Doc\]](#)

Sound

- Listening Temperature with Nano 33

[\[Doc\]](#)

Vibration

- Motion Recognition with RPi Pico
- Gesture Recognition with Wio Terminal

[\[Doc\]](#)

[\[Doc\]](#)

TinyML Application

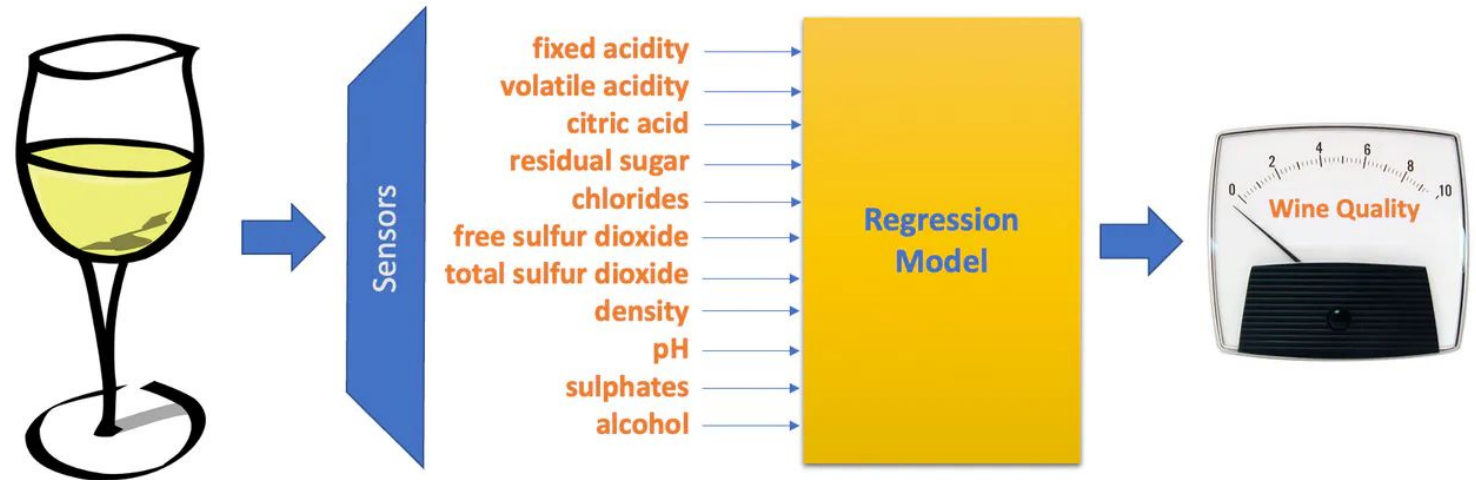
Examples (Regression)



Estimate Weight From a Photo
Using Visual Regression in
Edge Impulse



Regression on TinyML

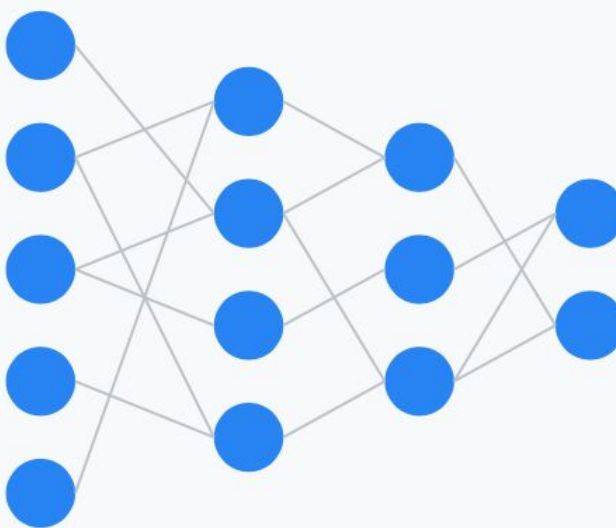


TinyML Made Easy: Exploring Regression - White Wine Quality

ML Lifecycle

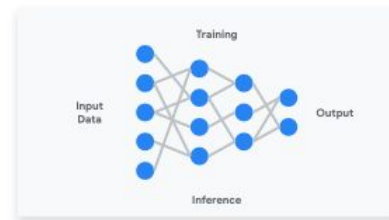
Training

**Input
Data**



Output

Inference



ML Code

**Data
Collection**

**Data
Preprocessing**

Debugging

**Resource
Management**

Optimization

Configuration

**Data
Verification**

ML Code

Model Analysis

**Serving
Infrastructure**

**Process
Management**

Automation

Feature Engineering

Monitoring

Metadata Management

AI Infrastructure

Data Engineering

Model Engineering

Model Deployment

Product Analytics

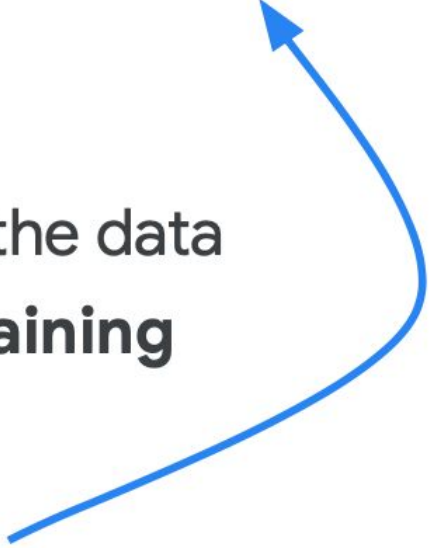
Data Engineering

- Defining data **requirements**
- **Collecting** data
- **Labelling** the data
- Inspect and **clean** the data
- Prepare data for **training**
- **Augment** the data
- Add **more data**

AI Infrastructure

Data Engineering

Data Engineering

- Defining data **requirements**
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- 

AI Infrastructure

Data Engineering

Model Engineering

- **Training** ML models
- Improving training **speed**
- Setting **target** metrics
- **Evaluating** against metrics
- **Optimizing** model training
- Keeping up with **SOTA***

* “**S**tate **o**f **t**he **A**rt”

AI Infrastructure

Data Engineering

Model Engineering

Model Deployment

- Model **conversion**
- **Performance** optimization
- **Energy-aware** optimizations
- **Security** and **privacy**
- **Inference** serving APIs
- **On-device** fine-tuning

AI Infrastructure

Data Engineering

Model Engineering

Model Deployment

Product Analysis

- **Dashboards**
- Field data **evaluation**
- **Value-added** for business
- Opportunities for **advancement** and **improvements**

AI Infrastructure

Data Engineering

Model Engineering

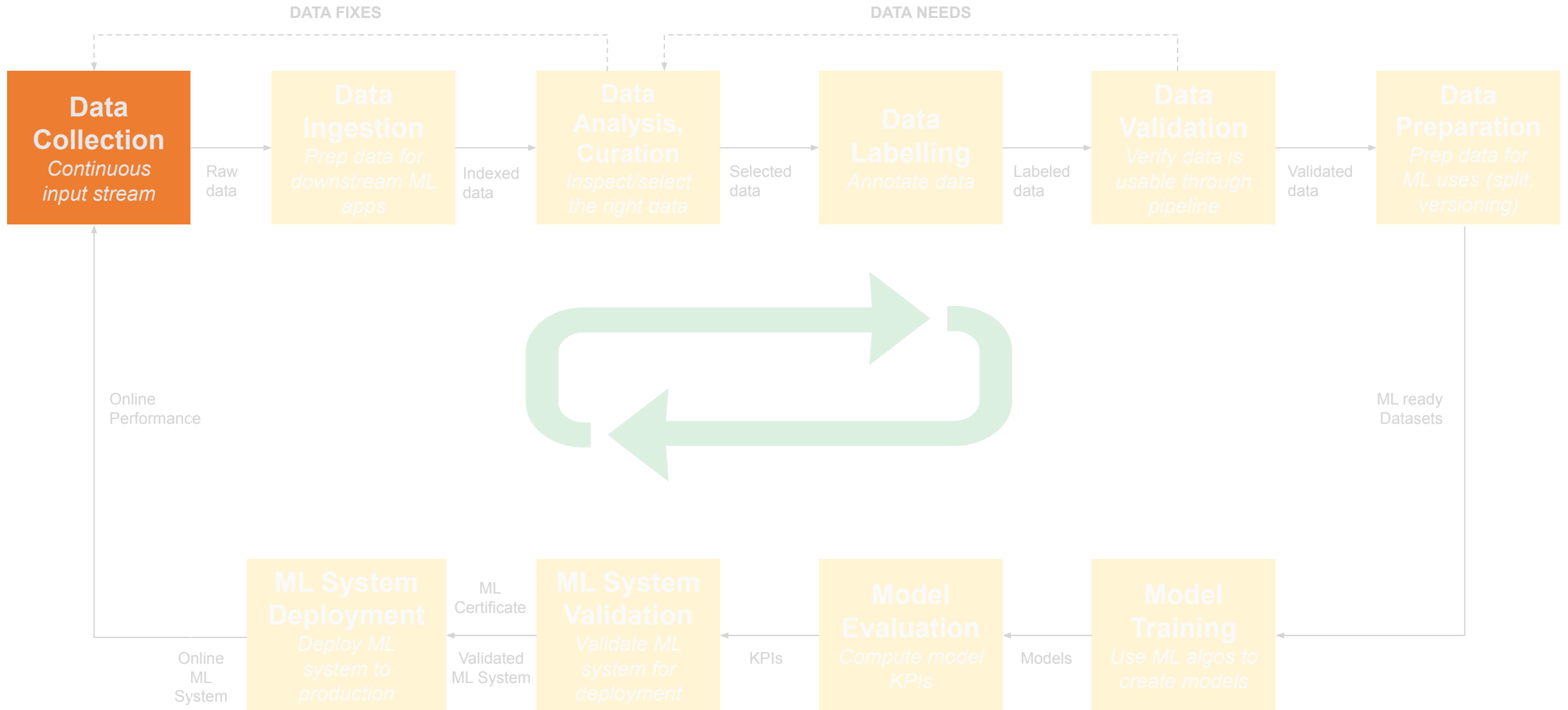
Model Deployment

Product Analytics

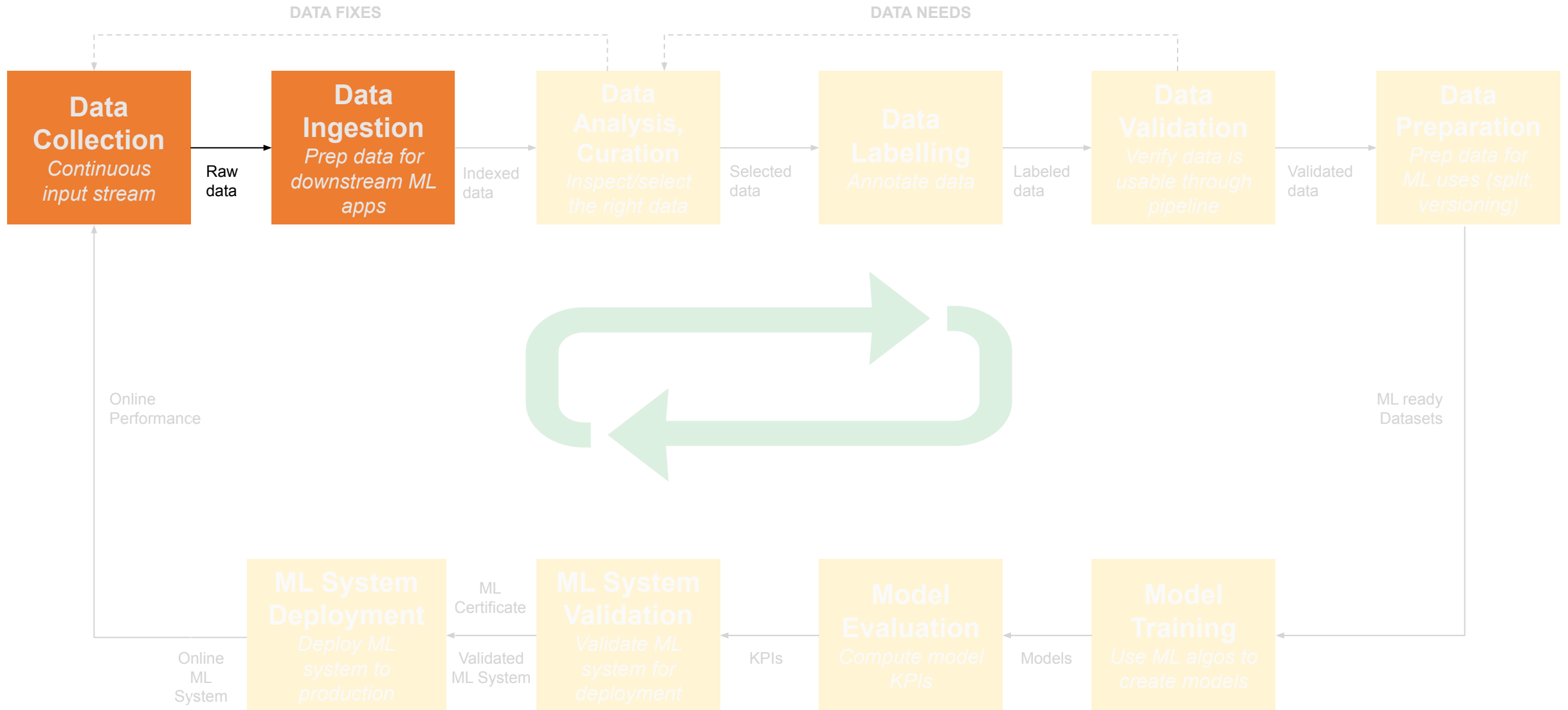
Focus in **TinyML**



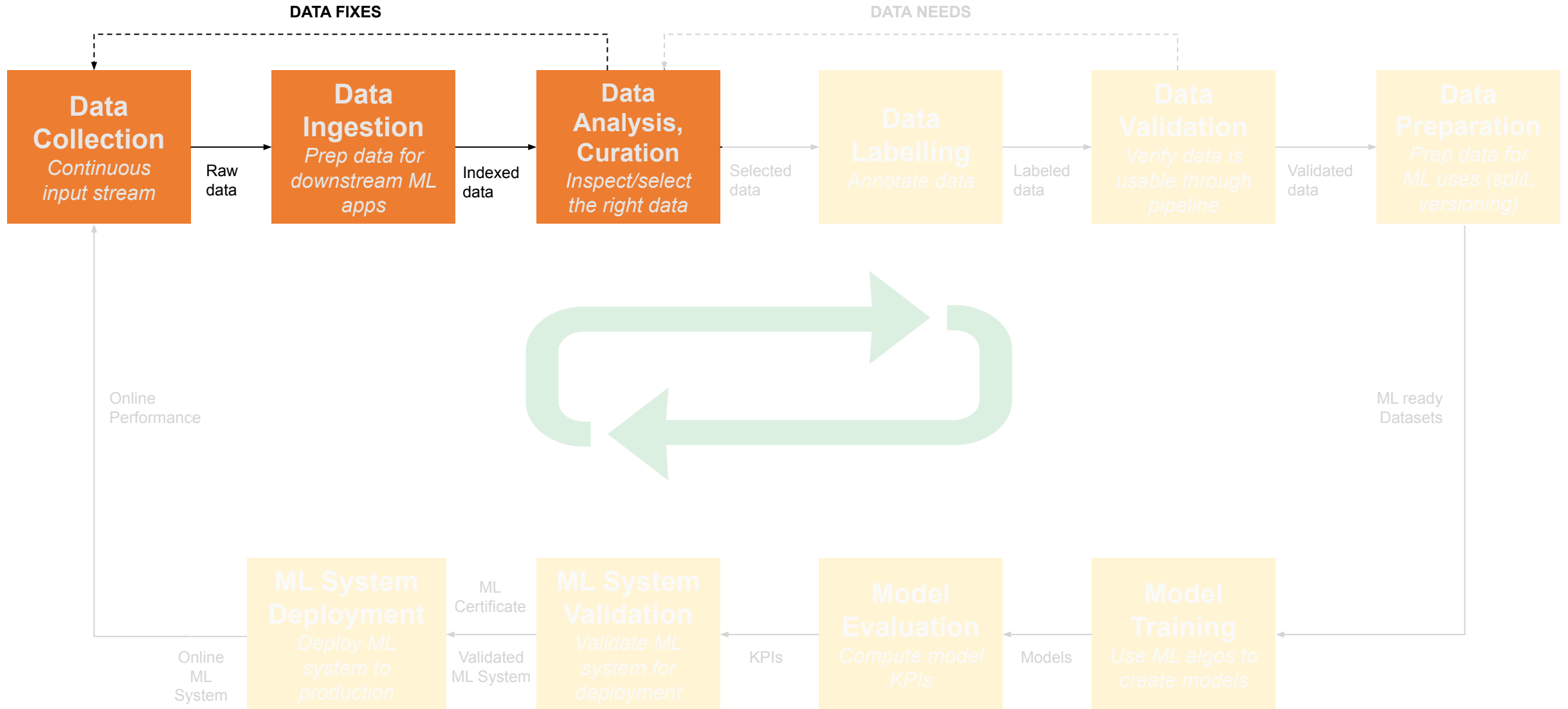
Life cycle of ML



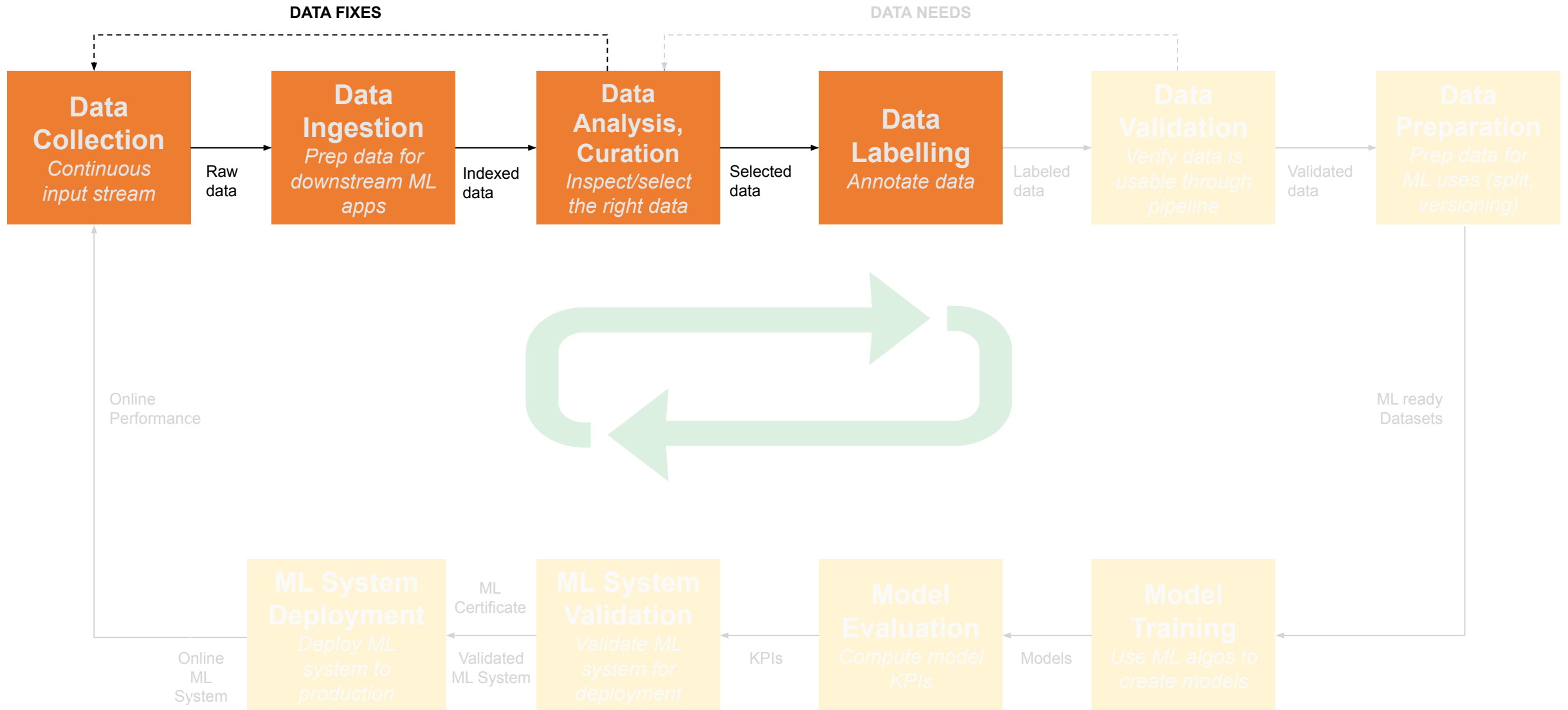
Life cycle of ML



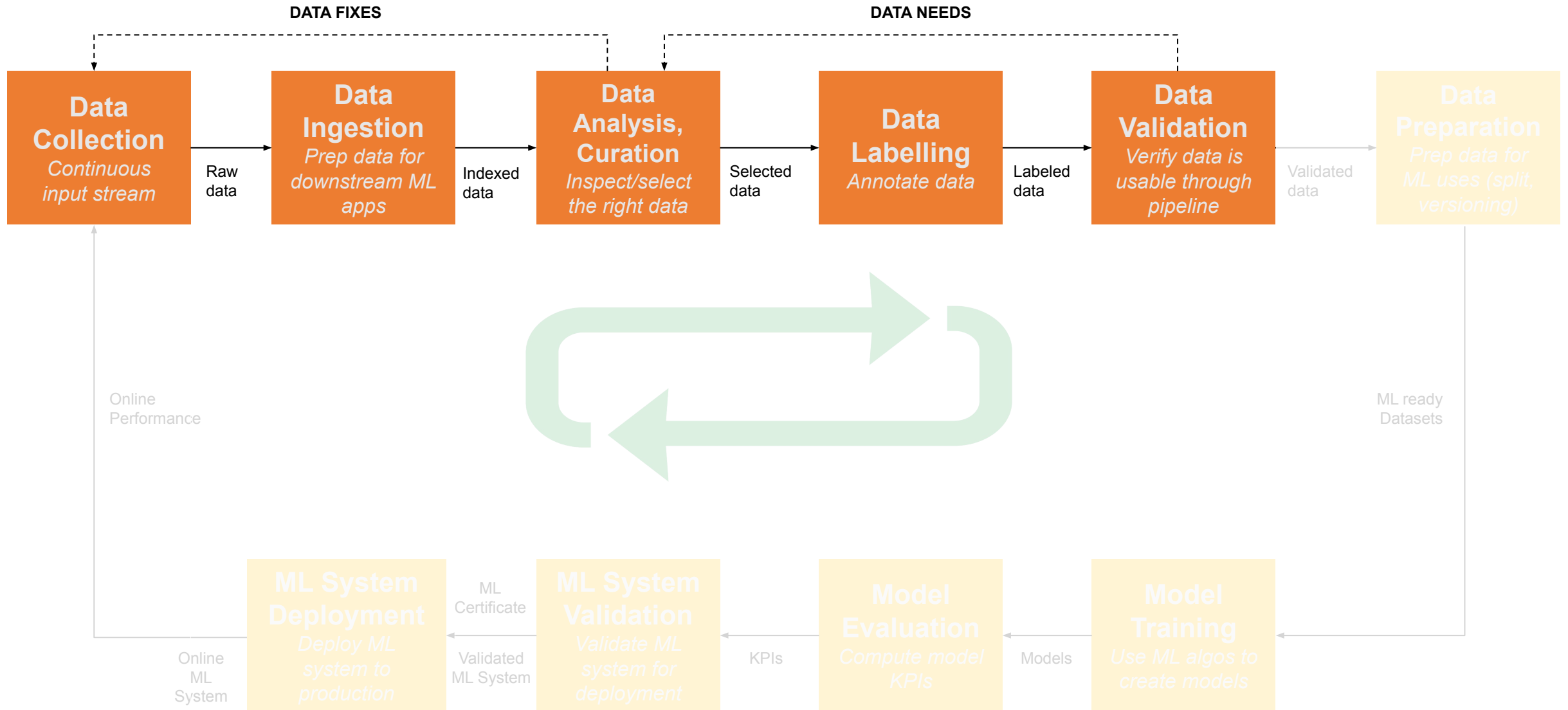
Life cycle of ML



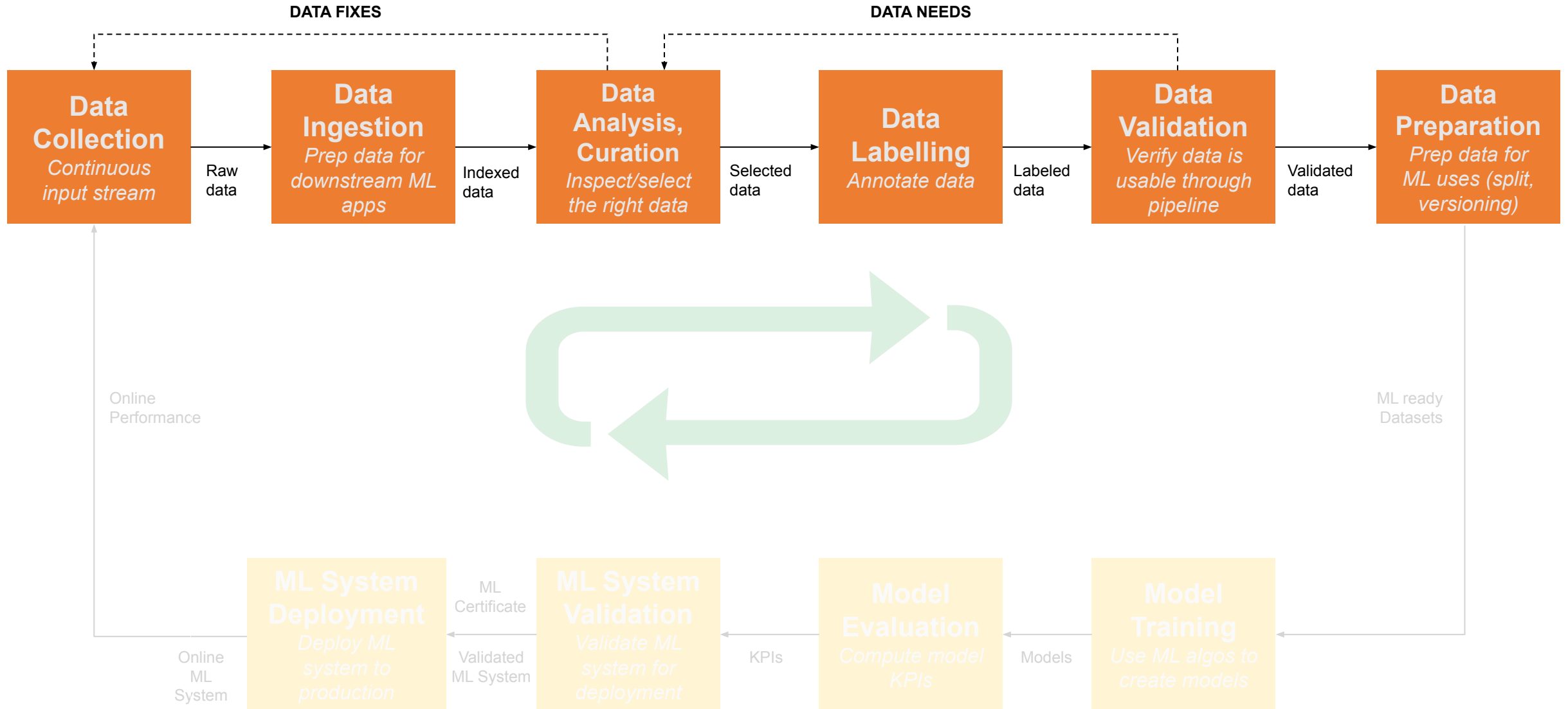
Life cycle of ML



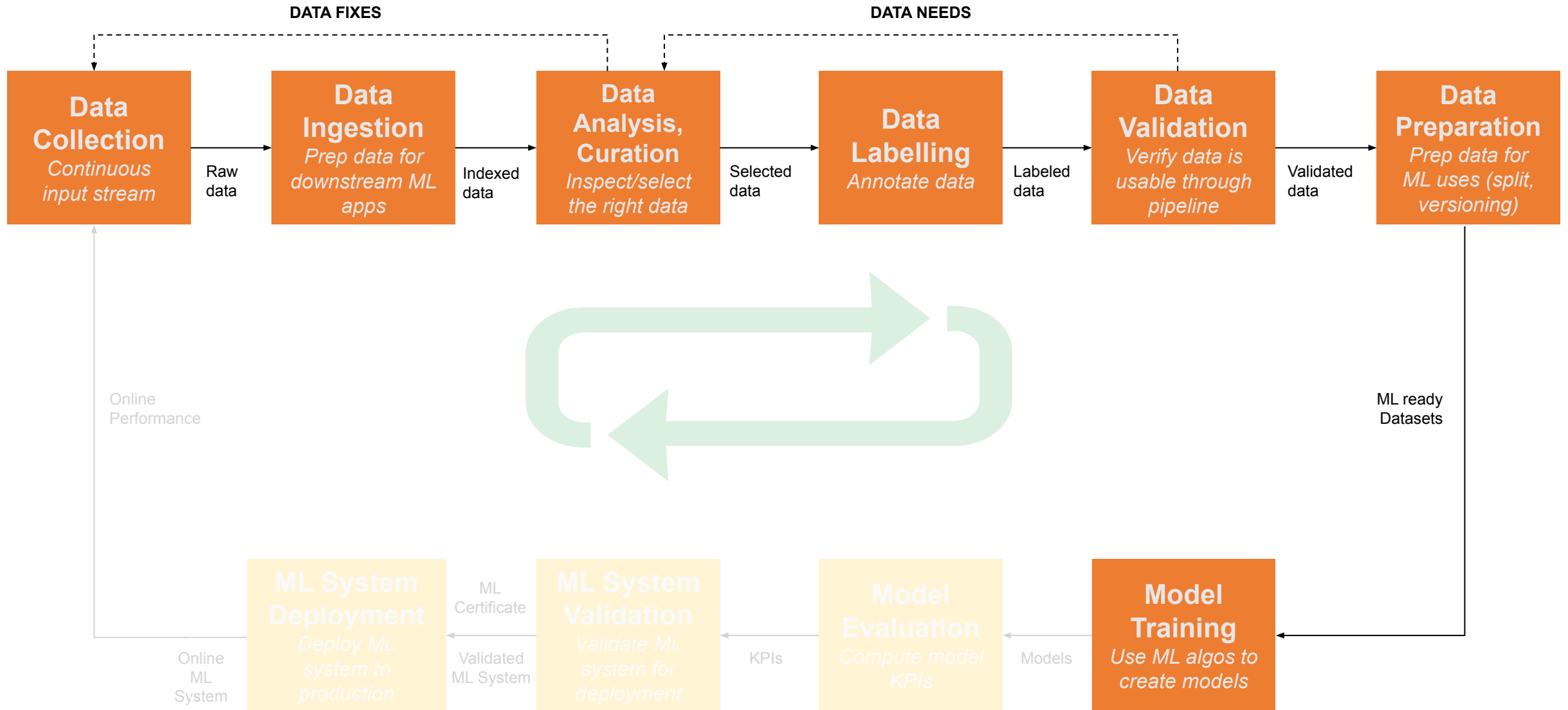
Life cycle of ML



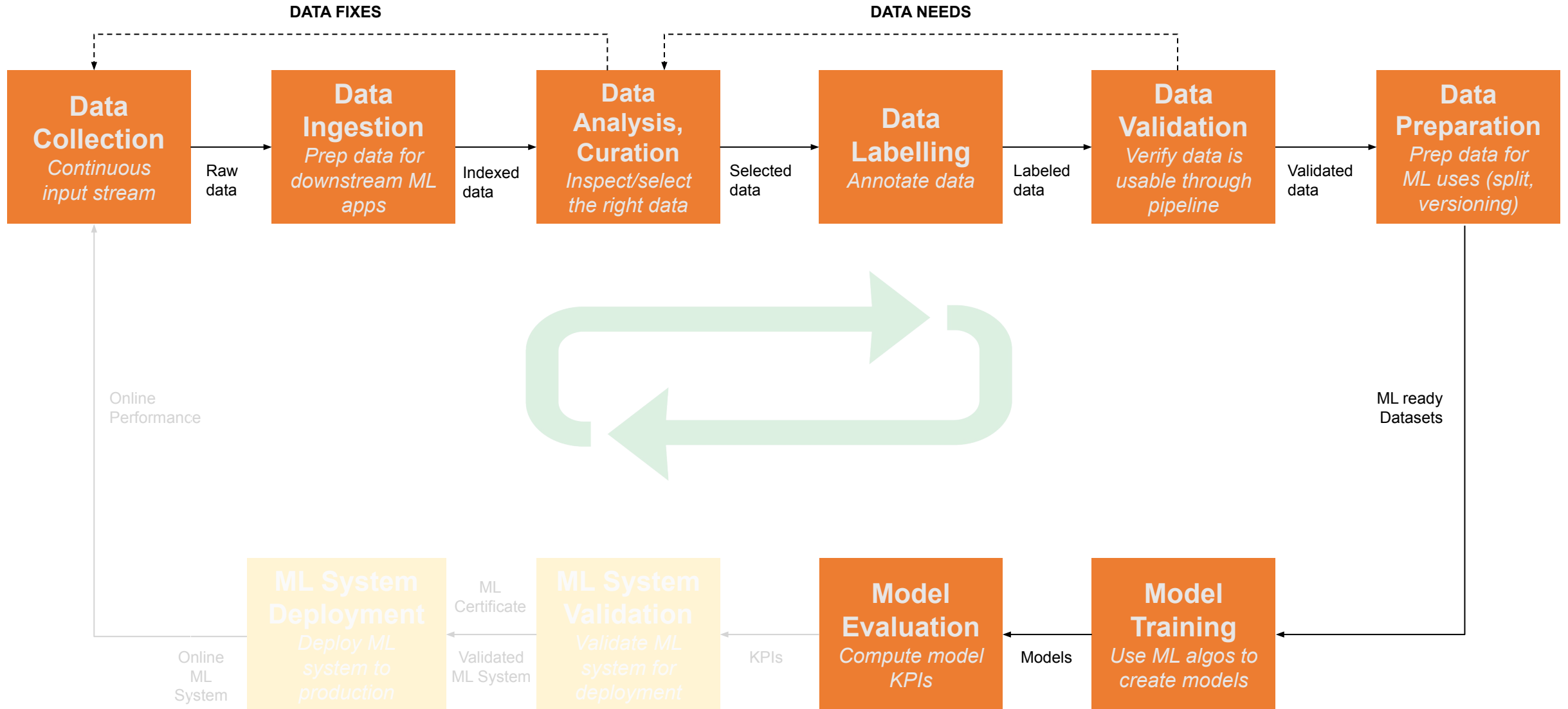
Life cycle of ML



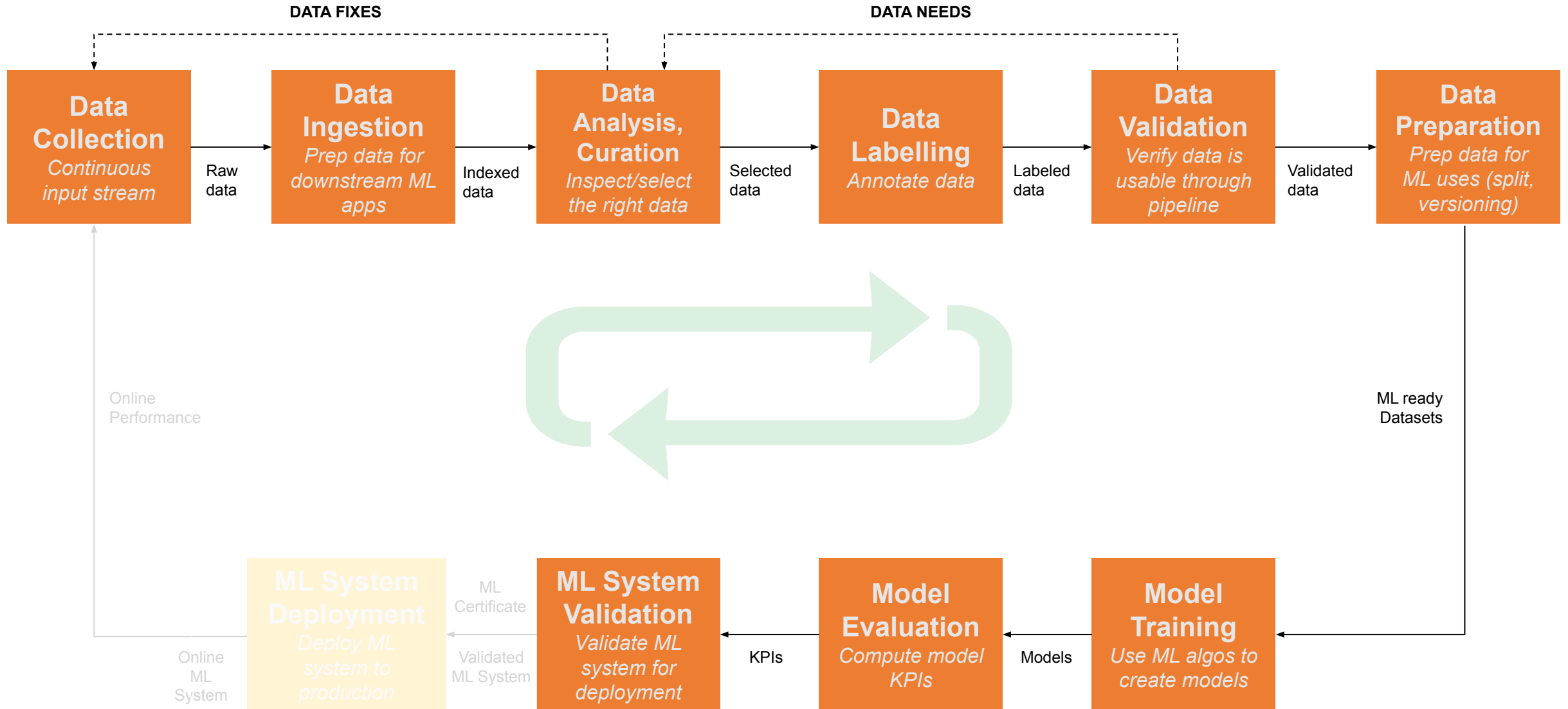
Life cycle of ML



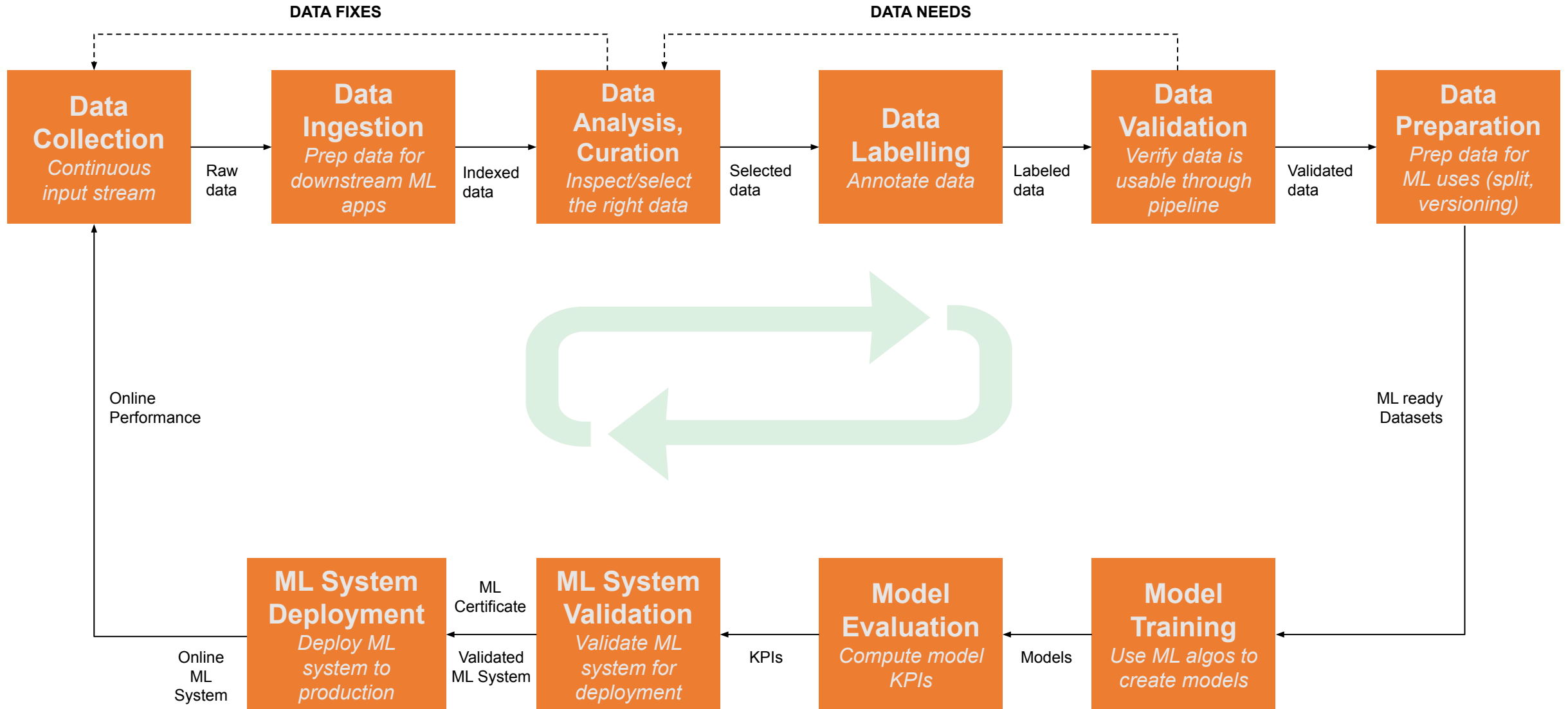
Life cycle of ML



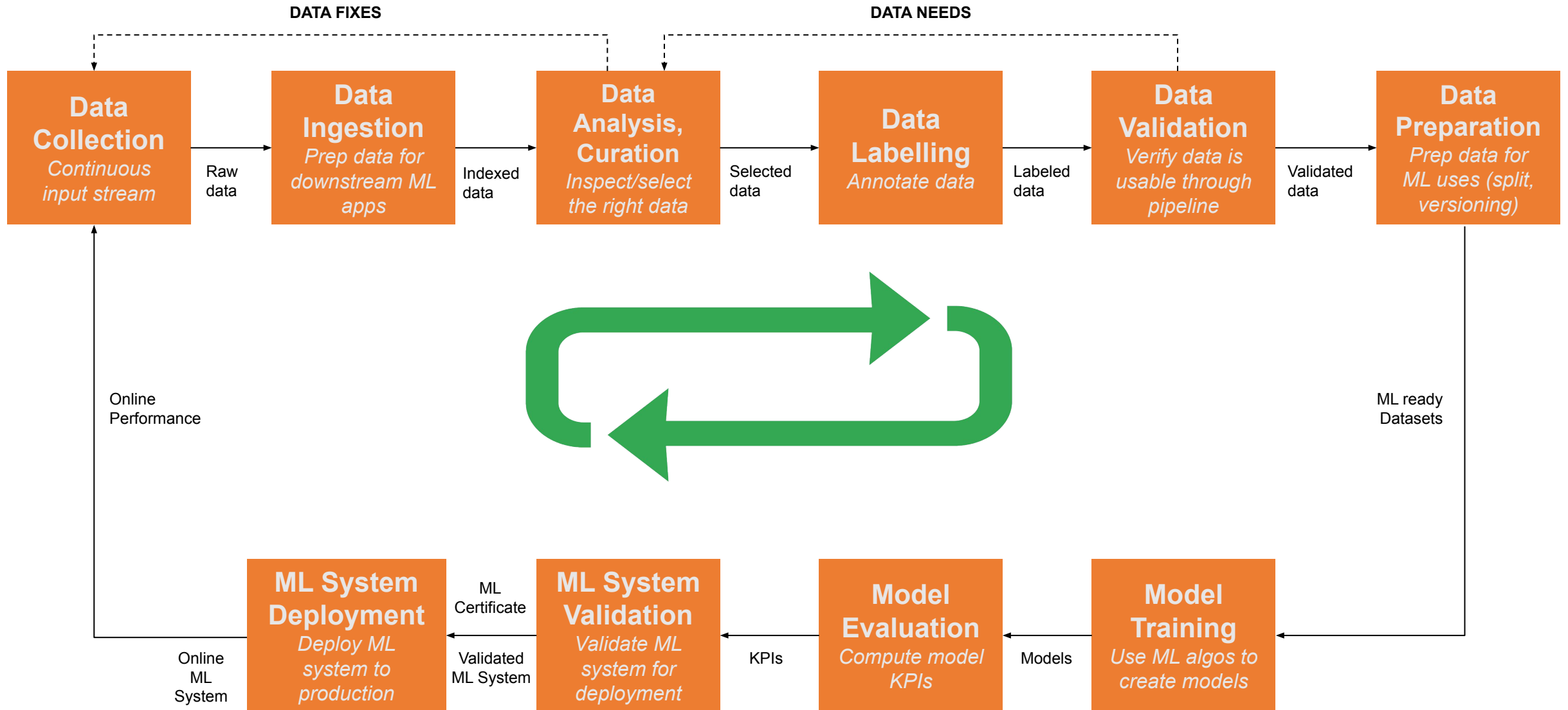
Life cycle of ML



Life cycle of ML



Life cycle of ML



ML Workflow

AI Infrastructure

Data Engineering

Model Engineering

Model Deployment

Product Analytics

Acoustic Sensors
Ultrasonic, Microphones,
Geophones, Vibrometers



Image Sensors
Thermal, Image



Motion Sensors
Gyroscope, Radar,
Accelerometer



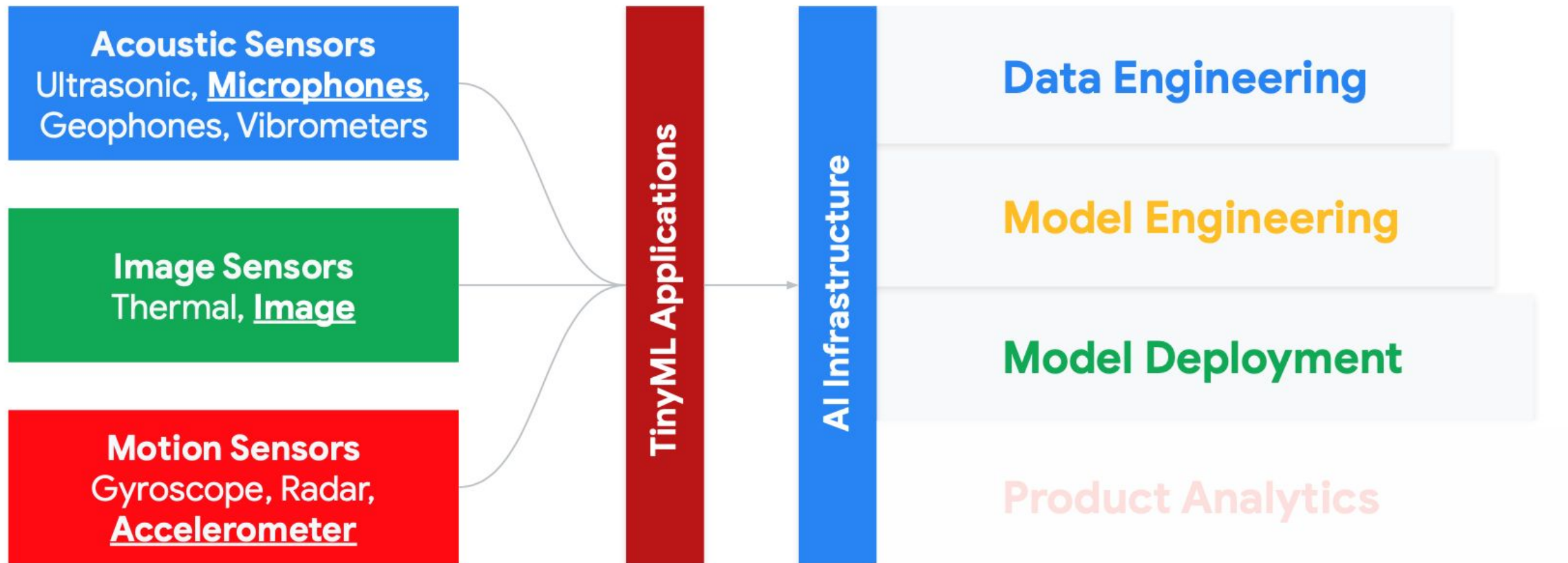
AI Infrastructure

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Model Engineering

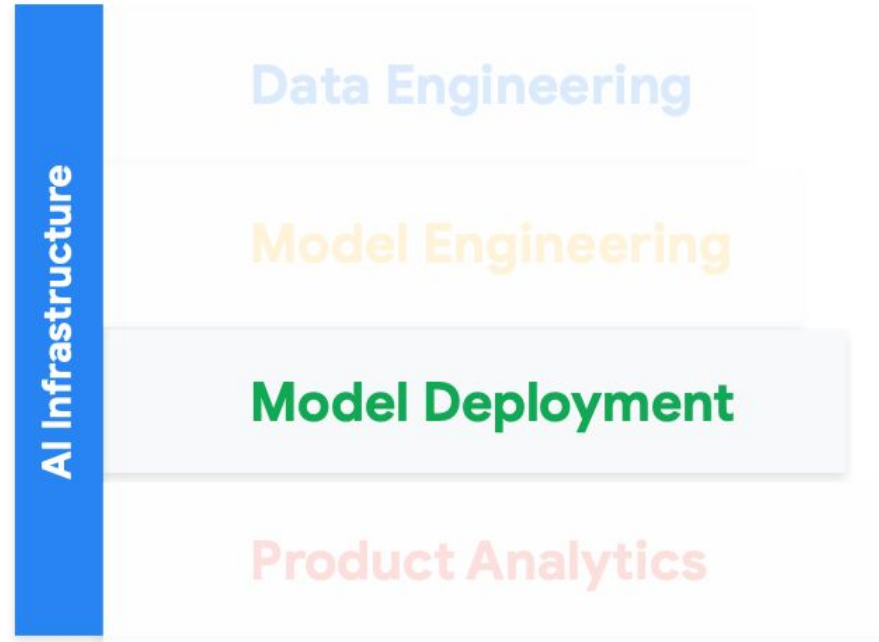
Model Deployment

Product Analytics

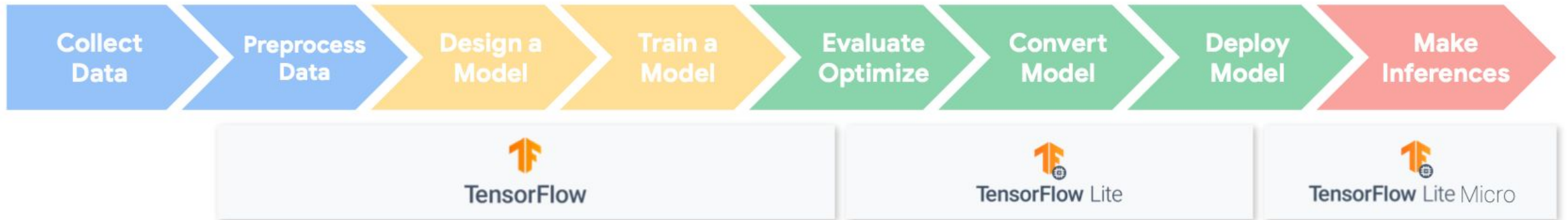


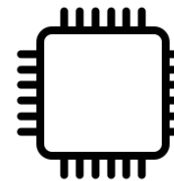
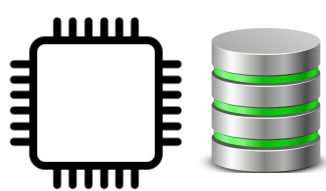












Data Engineering

Model Engineering

Model Deployment

Product Analytics

Collect
Data

Preprocess
Data

Design a
Model

Train a
Model

Evaluate
Optimize

Convert
Model

Deploy
Model

Make
Inferences



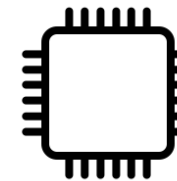
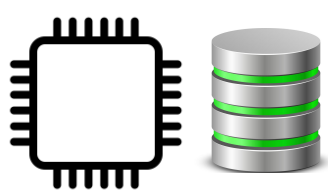
TensorFlow



TensorFlow Lite



TensorFlow Lite Micro



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TensorFlow



TensorFlow Lite



TensorFlow Lite Micro



theano



PyTorch

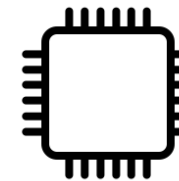
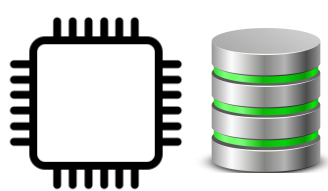
Caffe

uTensor



STM32
Cube.AI





Data Engineering

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Product Analytics

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TensorFlow



TensorFlow Lite



TensorFlow Lite Micro



theano



PyTorch

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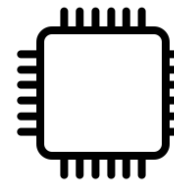
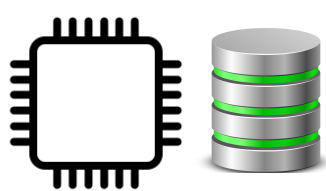
GLOW

STM32
Cube.AI

tvm



EDGE IMPULSE



Data Engineering

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Model Deployment

Product Analytics

Collect Data

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Make Inferences



TensorFlow



TensorFlow Lite



TensorFlow Lite Micro



theano



PyTorch

Caffe

uTensor

GLOW

STM32
Cube.AI

tvm



Intelligent Agent

Neutron



EDGE IMPULSE

Reading Material

Main references

- [Harvard School of Engineering and Applied Sciences - CS249r: Tiny Machine Learning](#)
- [Professional Certificate in Tiny Machine Learning \(TinyML\) – edX/Harvard](#)
- [Introduction to Embedded Machine Learning - Coursera/Edge Impulse](#)
- [Computer Vision with Embedded Machine Learning - Coursera/Edge Impulse](#)
- Fundamentals textbook: [“Deep Learning with Python” by François Chollet](#)
- Applications & Deploy textbook: [“TinyML” by Pete Warden, Daniel Situnayake](#)
- Deploy textbook [“TinyML Cookbook” by Gian Marco Iodice](#)

I want to thank **Shawn Hymel** and Edge Impulse, **Pete Warden** and **Laurence Moroney** from Google, Professor **Vijay Janapa Reddi** and **Brian Plancher** from Harvard, and the rest of the **TinyMLedu** team for preparing the excellent material on TinyML that is the basis of this course at UNIFEI.

The IESTI01 course is part of the **TinyML4D**, an initiative to make TinyML education available to everyone globally.

Thanks



UNIFEI