

# 4.4

---

## Optimisation of Soybean Manufacturing Process Using Real-time Artificial Intelligence of Things Technology

---

Ovidiu Vermesan<sup>1</sup>, Jøran Edell Martinsen<sup>2</sup>, Anders Kristoffersen<sup>2</sup>,  
Roy Bahr<sup>1</sup>, Ronnie Otto Bellmann<sup>2</sup>, Torgeir Hjertaker<sup>2</sup>,  
John Breiland<sup>3</sup>, Karl Andersen<sup>3</sup>, Hans Erik Sand<sup>3</sup>,  
Parsa Rahmanpour<sup>4</sup> and David Lindberg<sup>4</sup>

<sup>1</sup>SINTEF AS, Norway

<sup>2</sup>DENOFA AS, Norway

<sup>3</sup>NXTECH AS, Norway

<sup>4</sup>INTELLECTUAL LABS AS, Norway

### Abstract

In this article, a soybean process optimisation solution using real-time artificial intelligence of things (RT-AIoT) technology at the edge is presented. Image classification, object detection and recognition are machine vision techniques implemented into industrial internet of things (IIoT) devices to determine variations in the morphological features in soybeans. Evaluating soybean features, such as moisture and temperature combined with other measurements, such as colour, size, shape, and texture, can improve the utilisation of the raw material and the quality of the derived products, thus reducing energy consumption. Implementing intelligent vision locally on IIoT edge devices solves several issues faced by deploying it to the cloud and brings further challenges posed by deep learning on resource-constrained edge devices. Most deep neural networks are too complex to be created and trained on most nowadays microcontrollers, but if optimised in terms of memory, processing, and power capabilities, they can run on them. With multi-image sensors, and IIoT devices under evaluation, the

proposed production optimisation system is interfaced with the existing industrial SCADA system, and analyses the IIoT sensor data at different edge computing granularity levels. With the preliminary findings and results, we show that the RT-AIoT, including machine vision technology, is now possible on all micro, deep and meta edge levels with the advent of AI.

**Keywords:** production optimisation, artificial intelligence, smart sensors systems, edge computing, industrial internet of things, industrial internet of intelligent things, soybeans manufacturing, machine vision, machine learning, deep learning, SCADA, PLC, real-time artificial intelligence of things (RT-AIoT).

#### 4.4.1 Introduction

The digitising industry brings about the integration of the physical and digital systems of the production environments. It allows the collection of vast amounts of information using supervised control and data acquisition (SCADA) systems comprising programmable logic controllers (PLC), sensors/actuators and industrial internet of things (IIoT) devices [1][2]. These devices are connected to different equipment located in various production facilities, measure and monitor several parameters and process the data in on-premises servers and the cloud. The new technologies integrate people, machines, and products, enabling faster and more targeted information exchange. The information insights and analytics are increasing in value by implementing artificial intelligence (AI) techniques and methods collected by IIoT systems and processing at the edge close to the industrial production line. The data intelligent edge processing can bring valuable information and knowledge from the manufacturing process and system dynamics. By applying analytics and AI-based approaches based on data collected from IIoT devices, it is possible to obtain interpretive results for strategic decision making for process optimisation, cost reduction and energy-efficient process tuning.

Food processing and manufacturing include all processes intended to transform raw food materials into products suitable for consumption, cooking or resale. Implementing AI, IIoT and robotics solutions in the food processing and manufacturing sector can assist in overcoming critical issues related to production and execution by eliminating the possible chance of human errors and reducing the work redundancy being performed by manual labour.

Furthermore, innovation in production optimisation, production parameters tuning, and equipment maintenance can be fuelled by AI.

In soybean production facilities, the benefits of AI can be leveraged by using IIoT, neural networks (NNs), machine learning (ML) techniques, advanced analytical tools, image, and pattern recognition technologies to optimise production, equipment maintenance timely and less costly and overall production flow. With AI and IIoT, the data received from sensors are interpreted and recognised when action is needed. Aggregated data are generated and sorted, and significant data points are identified by sensors and AI techniques. These technologies are used to optimise processes, spot anomalies, such as early warning signs that equipment or motors may fail or require maintenance. AI technology is used to recognise patterns, expand the knowledge base, identify cause-and-effect relationships, and use insights related to likely outcomes or the next data point in the curve of the trend.

The Real-time Artificial Intelligence of Things (RT-AIoT) is the combination of AI technologies with the IIoT devices and infrastructure to achieve more efficient real-time IIoT operations, improve human-machine interactions and enhance data management and analytics.

In this article, an approach to optimising an industrial soybean manufacturing process using AI-based methods and RT-AIoT technology is presented.

The article is organised as follows. This section provided the introduction and the background for this research and innovation activity. The next three sections give an overview and a description of soybean production process, reference architectural conceptual framework, and process parameters monitoring techniques. The micro, deep and meta edge concepts are described in the next section. Afterwards, the section on embedded intelligent vision and multi-sensors fusion approach describes the system requirements, including an overview of relevant hardware architectures. The experimental set-up section depicts the overall architecture and workflow, the specific experiments performed and results. Finally, the last section concludes and highlights the next steps.

#### **4.4.2 Soybean Production Process Description**

For the use case presented in this article, the soybean production starts with 30 000 tonnes of soybeans arriving at the manufacturing facility on ships every three to four weeks.

The ships are unloaded in 3–4 days into a flat storage container, where the soybeans are stored until they are processed.

From the storage, the soybeans are transported on a conveyor belt into the cleaning area of the plant. Here, the coarse fraction and dust from the soybeans are cleaned out.

The cleaned soybeans are moved through a weight in which the budget capacity is 59 tonnes per hour.

In the next step, the soybeans are cracked between two pairs of cracker rolls, where each bean is broken into 6–8 pieces. The cracked soybeans are transported in closed conveyors and through a conditioning phase where the soybeans are heated and dried before flakers. The soybeans become more elastic in this process, so they do not crack in the flaking step. The flakers press the soybeans into thin flakes between a pair of hydraulic rollers.

The next phase is the expander process, where direct steam is added to the flakes, pressing the soybean flakes to a conus with a high-pressure screw to expand the oil cells in the soybeans. After the expander phase, the water content is increased due to the added direct steam, and the expanded material is dried with hot air before extraction.

In the extraction process, soybean oil is extracted from soybeans with hexane. Then, the hexane and soybean oil mixture is pumped to the distillation, and the soybean meal is transported to the toaster and heat treatment.

During distillation, hexane is evaporated from the soybean oil in three steps. After the hexane is removed, the soybean oil is pumped into a degumming phase. Here, water is added to separate lecithin from soybean oil.

After separation, the two products are pumped into separate dryers to evaporate the water, and then the products are pumped into storage tanks.

The soybean meal must be toasted and heated to evaporate hexane, eliminate bacteria, and make the meal digestible. After toasting, the meal is hot air-dried and transported to a storage container.

The soybeans production flow is presented in Figure 4.4.1.

The products resulted after different phases of the production are illustrated in Figure 4.4.2.

The soybeans are shipped from Brazil and Canada, with temperatures fluctuating from 5°C to 35°C. With the variation in raw material, product yields and energy consumption in soybean production are affected.

Using sensors, IIoT devices, and AI-based techniques makes it possible to control variations throughout the process to optimise product yields and

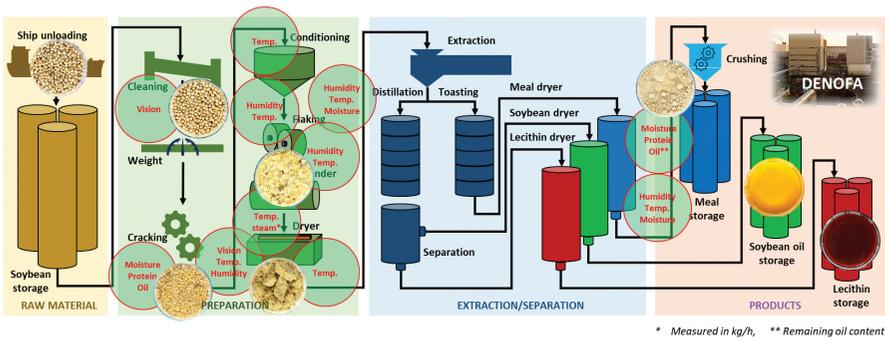


Figure 4.4.1 Soybean production process flow.



Figure 4.4.2 Soybean products.

energy consumption. Typical parameters monitored during the manufacturing process are temperature, moisture, colour, texture, weight, and volume.

Water content, also known as moisture, is the most critical parameter in preparing soybeans before the extraction phase. If the water content is too high, the residual oil in the soybean meal will increase, and the oil yield will be reduced.

This process is crucial for optimisation, and suitable locations are identified for instrumentation in cleaning, cracking and after-drying production areas.

The cleaning and preparation environment are dusty and challenging for moisture measurement and monitoring. Therefore, unique solutions must be considered for implementation.

### 4.4.3 Overall Manufacturing System Architecture and Platform

The soybean process optimisation solution is developed in the AI4DI (ECSEL JU) project [3]. The AI4DI reference architecture is defined at a high-level abstraction with various functional domains that include different devices, equipment on several communications networks, processing and storage capabilities at the edge and in the cloud, and training/learning embedded in different layers. The reference architectural conceptual framework includes different views, functional domains, system properties, cross-cutting functions, the description of interfaces and interactions between these elements and the features located outside the reference architecture [4].

This article uses the proposed implementation of the optimisation procedure for an industrial soybean manufacturing process using AI-based methods and RT-AIoT technology for mapping it into the functional domains. The high-level reference architecture includes six functional domains. A short description of each functional domain is provided in the next paragraphs.

**The physical systems domain** consists of physical components such as IIoT devices operating within soybean industrial manufacturing.

**The control domain** interfaces the physical systems using sensing and actuation in soybean industrial manufacturing, and implements necessary communication and means of execution. This domain includes the communication function (e.g., abstraction of different types of physical/link layer/networking technologies, Bluetooth, LoRa, Wi-Fi) with which the different sensors, actuators, and support infrastructure (gateways, controllers, routers, etc.) connect to exchange data, messages, and information.

**The operations domain** encompasses the provisioning, management, monitoring, diagnostics and optimisation of sets or groups of devices in the control domain, ensuring the continued operations of single devices and the associated control systems for soybean manufacturing. The domain includes provisioning, deployment, management, monitoring, diagnostic, predictive and optimisation functions implemented in on-premises edge computing facilities.

**The information domain** implements the collection, system-level data fusion, transformation, storage, optimisation, and analysis of data from several domains, and implements AI techniques and methods for intelligence fusion at the system level during different soybean manufacturing and

production stages. The analytics function includes data modelling, processing and analysis and the rule engines for different feature implementations.

**The application domain** uses case-specific logic, rules, integration, human interfaces, and models to deliver the system-wide optimisation of operations and relies on intelligence from the information domain. The APIs/UI function presents the application's capabilities in the form of APIs for dashboards or use by other applications.

**The business domain** integrates information from applications, business system enterprises, human resources, customer relationships, assets, service lifecycle, billing and payment, work planning and scheduling to achieve the desired business objectives. The business domain for soybean manufacturing implements the functionality for the integration of AI/IIoT-specific functions and standard enterprise business support systems such as Enterprise Resource Planning (ERP), Product Lifecycle Management (PLM), Supply Chain Management (SCM).

#### 4.4.4 Process Parameters Monitoring

The following section gives a short description of the measurement techniques under evaluation for measuring soybean parameters and ambient conditions.

The techniques and methods [8][9] evaluated for moisture, protein, oil measurements, soybean colour, texture and pattern analysis, and ambient parameters (e.g., temperature, pressure) are presented below.

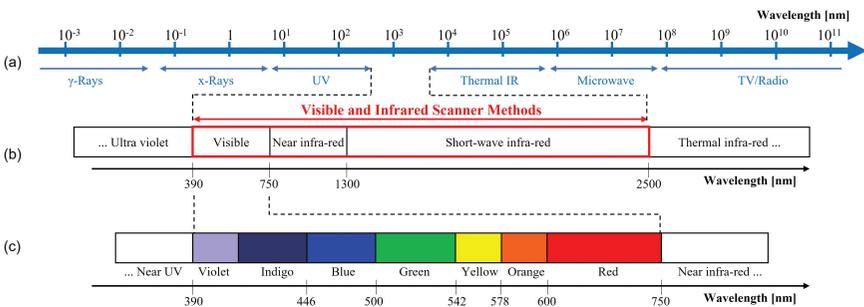
**Microwave non-destructive testing (MNDT)** is a non-invasive, non-destructive measurement technique in which microwaves penetrate a material and can thus be used to measure its water content (moisture). The dielectric constant of water changes with temperature and frequency, and is typically 20 times higher than that of other materials [5] at around 78.4 at ambient condition of 25°C and 1GHz [6]. This is resulting in a relatively strong interaction between microwaves and water, which is measured as attenuation and phase shift. The dielectric constant of soybeans thus influences microwaves, and the water content can be accurately determined. The equipment must use weak microwave power (typically 0.1mW) [7] so that the soybeans themselves are not heated or altered.

**Near-infrared (NIR) spectroscopy** is a non-invasive, non-destructive technique based on the absorption of electromagnetic radiation. NIR

spectroscopy instruments produce a large amount of data, and chemometric methods are used to extract useful information. Like many other measurements, those for NIR spectroscopy rely on standard calibration methods to achieve good results, and the instruments therefore need to be calibrated for the specific measurements that you want to perform—typically, a wide range of measurements, including highest and lowest levels of water, oil, or protein content, are needed. The possible bottlenecks of calibration versus the benefits to the demonstrator of the measurements are currently under investigation and there is yet no conclusion.

NIR light is a portion of the electromagnetic spectrum close to visible red, at about 750 to 2500 nanometres as illustrated in Figure 4.4.3, and can be used to detect the chemical bonds between atoms in organic compounds such as soybeans. Infrared absorption is caused by several effects, but the most important is the transfer of electromagnetic energy into chemical bond vibration, and absorption features may be related to specific molecular structures [10].

Soybeans absorb, reflect, and transmit varying amounts of near-infrared electromagnetic waves based on their composition. Each compound (e.g., oil, lecithin, and water) responds to a particular NIR wavelength, which can be measured to estimate the oil, water (moisture) and protein content in soybeans used to produce soy oil, lecithin, and meal. The quality of soybeans can be determined by their colour, shape, and chemical composition, and NIR technology can therefore help to identify and distinguish soybean quality based on chemical, oil, lecithin, and water composition.



**Figure 4.4.3** The electromagnetic spectrum - regions of interest in the context of NIR spectroscopy. Adapted from [10].

**Hyperspectral image analysis** is a non-invasive, non-destructive technique that is based on imaging of the electromagnetic spectrum, dividing it into many bands, and can be extended to a wide range of wavelengths beyond the visible range. Hyperspectral imaging measures continuous spectral bands and depends on relatively high computing power to transform the acquired pixelated images into readable data at an acceptable wavelength resolution. Optical filters and light sources are optimised for the wavelengths (bands) in the spectrum that reflect the levels of water, oil, and protein in soybeans. This method is being evaluated considering the complexity, cost, and calibration features.

**Capacitive sensing** is a non-destructive technique based on the same principle as a capacitor, measuring the electric field between two electrodes using a material placed between them as the dielectric. Applying an excitation voltage (DC or AC) to the electrodes creates an electric field, and the current flow in that field will change based on the conductivity of the material between the electrodes. The current is measured and transformed into values based on a physical model to give the moisture level of the material. This method is being evaluated for accuracy and other features.

**Cameras** can capture images in visible, infrared, near-infrared, hyperspectral spectrum to monitor the sizes and colours of whole soybeans and the texture of crushed soybeans. The image processing of crushed soybeans is more challenging than that of whole soybeans, thus requiring different types of cameras. Solutions for good lighting conditions are also needed.

**Temperature and pressure sensors** are used to measure the temperature in the different areas of the soybean processing line using wired/wireless sensors temperature sensors with a temperature range of 0°C to 55°C. The indoor ambient temperature and pressure vary according to location, weather conditions and seasons, and depends on the process steps performed in that area. Temperature and humidity are therefore critical parameters to measure and consider when analysing data from different points in a soybean production line.

AI and IIoT rely upon data generated at the sensor level, and data must be consistent, accurate and reliable. Sensors must have the required precision and embedded connectivity to pass measurement data for process optimisation purposes to the edge computing data system.

A common historian where information is aggregated for AI-based analytics, reporting and visualisation is needed to aggregate the data from the SCADA system and made it available for the edge server.

The value of AI and IIoT is limited by the ability to capture data from sensors in the soybean manufacturing process. The wired/wireless sensors must accurately measure moisture, temperature, humidity and other visual constituents, and the system should provide a way to confirm that the readings are accurate. This requires that the sensors are calibrated, and able to provide information when their battery life is low and a diagnose action is needed.

The process parameters monitoring includes a modular design for reliable sensing solutions in the harsh soybean manufacturing environment.

The sensor and related electronics are adequately packaged and placed in secure locations so they are not exposed to overrated temperature, humidity, dust, and other ambient conditions that can degrade and/or damage the sensors, IoT devices, gateways prematurely.

Power consumption is critical for the lifetime of the wireless sensors, the measurement precision of the sensors, and the AI-based algorithms applied to them. Therefore, viable power monitoring and energy-efficient communications capabilities must be integrated into the design.

#### **4.4.5 Edge Processing and AI-based Framework for Real-Time Monitoring**

Intelligent edge computing architectures accelerate the move to more processing and the value-creating process-optimisation use cases associated with the edge. The approach used in this work for soybean process optimisation addresses the granularity of the edge by providing intelligence to the micro, deep and meta edge. A description of the micro, deep and meta edge concepts are provided in the following paragraphs.

**The micro edge** describes the intelligent sensors, machine vision and IIoT devices that generate data and are implemented using processors and microcontrollers (e.g., ARM Cortex M4) due to constraints related to costs and power consumption. The distance from the compute resource is minimal, as the compute resources operate on the data they generate. The hardware devices of the micro-edge physical sensors/actuators generate data and/or actuate based on physical objects. Integrating AI-based elements into these devices and running AI-based techniques for training/learning and inference

on these devices brings the intelligence and analytics closest to the physical parameters measured.

**The deep edge** comprises intelligent controllers PLCs, SCADA elements, machine vision connected embedded systems, networking equipment (IIoT gateways) and computing units that aggregate data from the sensors/actuators of the IIoT devices generating data. Deep edge processing resources are implemented with performant processors and microcontrollers (e.g., Intel i-series, Atom, ARM M7+, etc.) that include components such as CPUs, GPUs, TPUs or ASICs.

**The meta edge** integrates processing resources, typically located on premises, implemented with embedded high-performance computing units, edge machine vision systems, edge servers (e.g., high-performance CPUs, GPUs, FPGAs, etc.) that are designed to handle compute-intensive tasks, such as processing, data analytics, AI-based functions, networking, and data storage.

The edge analytics applications presented in this work enable new use cases that rely on low-latency and high-data throughput. The demonstrator developed use intelligent sensors, embedded machine vision and IIoT devices integrated with edge computing to implement learning and inference on-premises in the soybeans manufacturing facility.

#### **4.4.6 Embedded Intelligent Vision and Multi-sensors Fusion Approach**

Image classification, object detection and recognition are machine vision techniques using information collected from IIoT sensors. With such information, it is possible to determine morphological features such as colour, size, shape, texture, and moisture in soybeans for monitoring and improving the utilisation of the raw material and the quality of the derived products, thus reducing energy consumption. With the advent of AI, this capability is now possible on all micro, deep and meta edge levels.

Intelligent devices are enabled by machine vision to grasp the visual surroundings. Machine vision is integrated into the perception systems in industrial sectors, including autonomous vehicles, food processing, semiconductors and more, and is one of the areas that has benefitted the most from the rapid advances in AI/ML. ML algorithms enable high performance

in image segmentation, object detection, image classification, object tracking, pattern and object recognition, image generation, and more.

Deep Learning (DL), a subset of ML, allows machines, robots and intelligent IIoT devices to recognise objects with close to human-like ability. At the lower levels, ML algorithms perform processing techniques on the image, extract features from the image, access and intertwine multiple views. At the higher level, they perform more advanced tasks, such as image classification - making inferences about whether the object in the image belongs to a specific class of objects. It is at the highest level that DL is employed to build intelligent, scalable machine vision systems that can recognise/identify and react/respond to objects in images and videos.

Convolutional neural network (CNN) is a class of DL networks and has become increasingly powerful in large-scale image recognition on IIoT devices by combining the feature extraction process and classifying the extracted features in the same algorithm, relying on extracted features. When DL technology is deployed in IIoT devices, it relies on pretrained DL models, and transfer learning techniques are employed to retrain an existing image classifier into a custom classifier by retraining a small image dataset using minimal resources. CNN is under evaluation along with other DL models and techniques.

Edge sensors and IIoT devices are increasingly becoming more intelligent, generating a massive amount of data, often creating latency, reliability, and privacy concerns. A shift in AI processing from the cloud to the edge was triggered by such developments, made possible by recent advances in microcontroller architectures and algorithm design. By deploying intelligent vision locally on IIoT edge devices, most concerns related to deploying to the cloud are addressed and answered:

- **Bandwidth:** ML algorithms need lots of data and transferring large amounts to the cloud is costly and demands bandwidth. Therefore, severe reductions must be applied, affecting the performance and accuracy of the results from the algorithms. When algorithms run on IIoT edge devices, the amount of data processed is limited only by IIoT edge device capabilities.
- **Latency:** ML models on IIoT edge devices can respond in real-time to inputs (as the round-trip to the cloud is no longer involved) enabling real-time edge nodes to run in real-time and meet deadlines.
- **Costs:** By processing data on-device, the costs of transmitting data over a network and processing it in the cloud are reduced. The cost of running ML in the cloud can be expensive due to the complex infrastructure.

- **Reliability:** Systems controlled by on-device models are inherently more reliable, not least because they are no longer affected by outages in the cloud.
- **Privacy:** User privacy is protected when data are processed locally on an embedded system and are not transferred to the cloud.

Nonetheless, other concerns are posed by ML on machine vision IIoT edge devices. Most deep NNs are too complex to be created and trained on most nowadays microcontrollers, but if optimised in terms of memory, processing, and power capabilities, they can run on them. The optimisation can be done either by rewriting the models in low-level languages or by quantising to improve the latency and the model size.

It is envisaged that it will be more common for machine vision IIoT edge devices to embed deep NNs and other AI techniques in the future. For now, thanks to interoperability efforts, tools and methods are available to optimise deep NN that have been trained on standard platforms to do specific tasks. Therefore, they can run on IIoT edge devices with limited capabilities. It is a matter of balancing the goals of obtaining the most significant reduction in the size of the original code with a minor accuracy loss.

Real-time monitoring and control are essential criteria for optimising process parameters and maximising soybean manufacturing production outcomes. The proposed process optimisation is built on an industrial real-time data acquisition AI-based system (intelligent sensors and machine vision IIoT devices) implemented into an on-premises edge computing environment integrated with existing industrial SCADA system. The remote soybean parameters are measured and collected by the intelligent data acquisition and control system through reliable protocols and communication networks, providing an interface with the existing SCADA system through a common historian entity.

In this context, multi-sensor fusion is the process of achieving multi-objective optimisation by combining data from multiple sensors, which, taken separately, can only provide local optimums.

The data aggregation functionalities are integrated into the edge platform components, whereas the IIoT gateway handles edge data collected from different IIoT devices. The IIoT hardware platform and devices are integrated with the existing SCADA system and open platform communications server (OPC), interfaced with the ERP manufacturing facility and web and mobile App solutions.

Monitoring the moisture of soybeans before processing is critical, and three process sub-systems are identified as possible locations in the processing workflow and contain component sensor instrumentation according to the sensor tag system developed for unique identification.

The moisture measurements and other monitoring measurements are seen in conjunction with temperature and image analyses. The targeted measurement parameters monitored are the moisture of soybeans before processing at different locations in the processing workflow (e.g., on the conveyor belt before cleaning, on the conveyor belt after cleaning and before weight, and after crackers before conditioning). The aim is to measure soybean water content, temperature and “quality of cracking,” to control the changes and adjust the conditioning according to the variations.

Different communication protocols and gateways are used (BLE, LoRa and Wi-Fi), depending on data rate, bandwidth, application, etc. Even in harsh environments, communication with edge devices is facilitated by the seamless integration of wireless connectivity, ensuring data storage, pre-processing in real-time, visualisation, and possibilities to change parameters or effectuate other necessary actions.

#### **4.4.6.1 Embedded Vision IIoT Systems Evaluation**

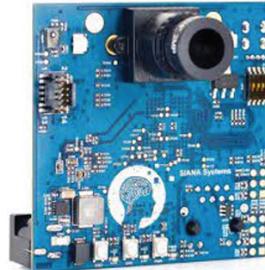
A broad spectrum of hardware architectures is available with various trade-offs to deploy machine vision NN models. Several architectures are under evaluation in terms of suitability for different machine vision applications and placement on the three edge levels. They are illustrated in Figure 4.4.4 and briefly presented in the following paragraphs.

**OpenMV** [11] is a small camera module on a microcontroller board that can be programmed in Python to implement applications using machine vision in the real world. It can detect colour and shape, frame differencing, face detection and more. For the experimental setup, the webcam capabilities have been enhanced with infrared and global shutter camera modules.

The former is to easily interface with the flare left in thermal imaging sensors for thermal vision applications. Combining machine vision with thermal imaging allows for better identifying objects to measure the temperature with great accuracy. Because of the modular design, the swapping of the standard lens for the long-range infrared imager can be done easily. The latter module allows the OpenMV Cam to capture high-quality greyscale images and not be affected by motion blur. The module can take snapshots on-demand with high frame-per-second speed.



OpenMV [11]



MPCam [12]



STM32MP157F-DK2 [13]



STM32H747I-DISCO(VERY) [14]

Figure 4.4.4 Hardware architectures under evaluation.

**MPCam** [12] is an intelligent camera system designed to bridge the gap between the development and rapid deployment of machine vision applications. The camera has, in addition to a Dual Arm<sup>®</sup> Cortex<sup>®</sup>-A7 core running up to 800 MHz and Cortex<sup>®</sup>-M4 at 209 MHz combined with a dedicated 3D graphics processing unit (GPU) and MIPI-DSI display interface and a CAN FD interface, an accelerator module that balances performance and cost and is therefore suitable for lab experiments as well as in the production line.

**STM32MP1** [13] is a multiprocessor system that allows independent firmware to run on two computer cores (MasterArm Cortex-A7 running Linux based operation system and Arm Cortex-M4 running RTOS). The latest Linux includes TensorFlow Lite (TFLite), so the development kit can run TFLite models. It has no dedicated computer unit for AI, and as such, inferences can only be performed using its CPU unit. However, the board can add an accelerator (such as Coral USB accelerator) to speed up the inferences of AI models. STM32MP1 is compatible with the Deep Learning STM32Cube.AI ecosystem.

**STM32H747I-DISCO** kit [14] is designed with STM32Cube.AI, an extension pack of the STM32CubeMX configuration and code generation tool and function packs for high performance AI applications. It is now possible to map and run pretrained networks on the board of the microcontroller using several AI solutions. The function pack for computer vision features examples of computer vision applications based on CNN, including an application for food recognition.

Regardless of the type of hardware architecture, the solution allows the import of trained neural networks and convert them into microcontroller code and run the inference directly on the microcontroller on edge. This reflects the AI paradigm shift, going from the cloud approach with high bandwidth, high centralised processing power, high latency, to more distributed AI, with lower bandwidth and reduced centralised computing power, more real-time response, and improved privacy.

#### **4.4.7 Experimental Setup**

In the first phase of the soybeans production optimisation, the specific objective is to evaluate variability in the morphological features of soybeans and classify soybeans according to selected features. The concept is to build an embedded intelligent vision system integrated into the production line as part of an advanced IIoT concept that can detect soybeans (wholes and fractions) and analyse their morphological features. The system can be used to detect variations that can lead to production process adjustments to improve final product quality and optimise the process in terms of energy reduction.

The embedded vision system is a flexible machine vision platform integrated into the IIoT system that will instantly, when powered on, display interactive results in real-time.

The OpenMV-based experimental setup currently under evaluation is illustrated in Figure 4.4.5. The system consists of multiple OpenMV nodes acting as machine vision IIoT devices. The OpenMV comes with a removable camera module, making the interface with different vision sensors possible. Some nodes are equipped with a global shutter camera module to capture fast action and eliminate motion blur, while others use the infrared camera module for thermal machine vision.

The nodes are mounted strategically on the production line (before and after the soybeans are cleaned out and after they are crushed). The machine

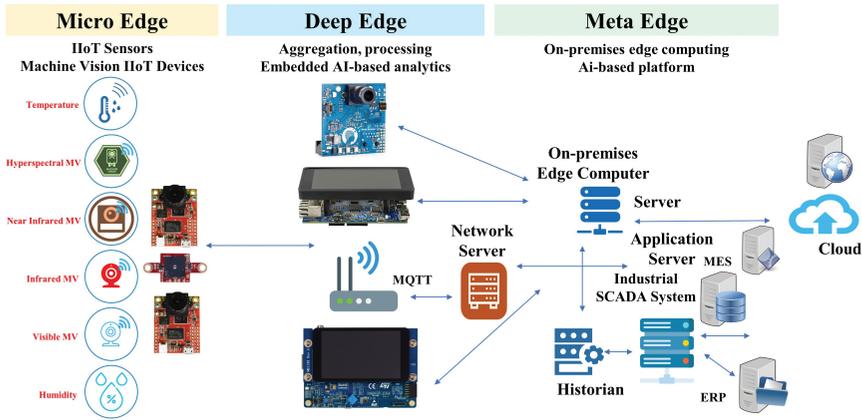


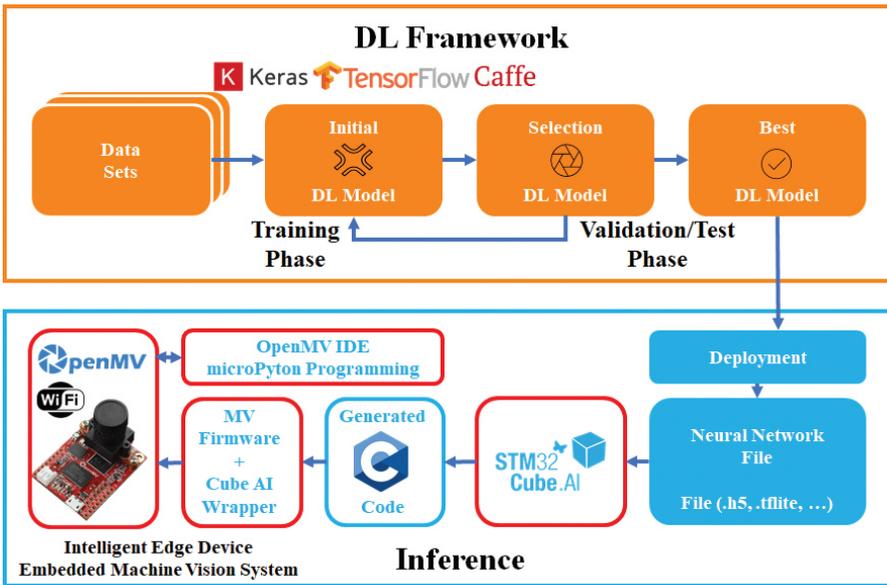
Figure 4.4.5 Experimental setup.

vision IIoT devices will be placed over the conveyor belt or in places that view the crushed soybeans.

The OpenMV machine vision IIoT devices are used not only as image sensors but also as AI-based processing nodes. The OpenMV IDE includes a Python-based interface to develop application code and programme the machine vision functions. The IDE is a robust editor and offers a frame buffer viewer to see what the camera sees, a serial terminal for debugging, and a histogram display for making object detection and tracking easy. The application is then sent as a script to the camera module, which is running MicroPython.

The OpenMV machine vision IIoT devices can run NNs on images, and deep learning NNs can run inference layers. As such, they do not need a network connection for inferences for the AI functionality. Some nodes are equipped with Wi-Fi modules using limited bandwidth to transmit via MQTT all protocol-specific measurements and results to the higher edge layers (deep and meta edge) for multi-sensor fusion and further processing.

The OpenMV offers competitive performance at low power consumption. Still, the nodes have limited flash memory (2 MB) required to store the firmware, and the NNs files. The memory can be expanded using an SD card, resulting in a slower inference output.



**Figure 4.4.6** Training and inference workflow.

As the soybean application is relatively large, the approach is to optimise the size, and the optimisation flow under evaluation is presented in Figure 4.4.6.

The NN model’s creation, training, and validation are performed using ML frameworks, and several tools are under evaluation (Keras, TensorFlow and Caffe). The trained NN model is then input to the STM32Cube.AI module and converted into optimised C code. Next, the firmware wrapped with the generated files and NN library is compiled, and the binary file is flashed onto the OpenMV target using IDE. The model is then used to programme the board (using microPython) and call the NN prediction function. The advantage of this workflow is that it performs the hardware level optimisation, and it also provides access to the software stack.

Notably, if the resulting optimised code still does not follow the hardware capabilities, the optimisation process is repeated with more compression. The process is about reaching a balance between avoiding opting for more performant hardware (resulting in increased costs) and not jeopardising the application’s performance (e.g., results accuracy). Although not shown in the Figure 4.4.6, it is envisaged to use the above flow in a feedback loop, where

relevant runtime data is sent back to the framework to retrain the NN model and redeploy it in real-time back onto the microcontroller.

#### 4.4.7.1 Experimental Evaluation and Results

In real-time, soybeans will move in a bulk fashion on the conveyor belt under machine vision IIoT devices. Both bulk and individual soybean samples must be considered. The preliminary experiments were conducted mainly on soybean samples to sense soybean colour, shape, and soybean amounts. The following guidelines govern the machine vision objectives:

**Origin** - Soybean size in the same load can vary, for example, due to different suppliers. There are relatively large variations in seed shape, size, and colour. Shape varies from almost spherical to flat and elongated. Seed size ranges from 5-11 mm and seed weight from 120-180 mg/seed. Soybean hulls can be yellow, green, brown, or black, either all one colour or a pattern of two colours [15]. For the use case presented in this article there are mainly two types of soybeans (originating from Canada and Brazil), and the former tends to be slightly larger than the latter.

**Dockage fractions** - A load also contains dockage fractions (including split soybeans due to breakage) that must be removed during the cleaning process. The percentage (%) of these fractions is an important indicator of soybean quality. The amount of broken soybeans smaller than halves should be determined.

**Colour** - Colour differences may relate to a moisture content variation.

**Moisture** - Investigating the impact of moisture content on the morphological feature classification of soybeans, individual and bulk, is important at different moisture content levels.

**Crushed fractions** - Soybeans are crushed and analysed. Each targeted fraction present in the sample should be distinguished based on images. Currently, this is performed manually based on three target values (3.36mm, 1.69mm, 0.84mm), resulting in four fractions:  $> 3.36$  mm,  $> 1.69$  mm,  $> 0.84$  mm,  $< 0.84$  mm. The results provide a measure of the decrease in soybean oil quality with increasing soybean breakage.

The challenge is the variation in soybeans' morphological features, which are extracted as attributes for classification using image processing techniques and neural networks. Around 50 data sets are collected with a fixed number of soybeans (60) randomly arranged in an imaginary cell size of 80 x 80 mm.

All images were captured with the OpenMV device and pre-processed within the IDE before saving them. The camera can capture up to 320x240 RGB565 images. The saved images are split into training and testing data sets and fed to training and validation. Various machine vision functions, including neural networks, are performed, on the images, including the following:

**Boundary detection** - This technique uses the Canny Edge Detector algorithm and simple high-pass filtering followed by thresholding. Boundary detection indicates the presence of dockage fractions before cleaning.

**Colour tracking** - The OpenMV device can detect up to 32 colours simultaneously in an image, and each colour can have any number of distinct blobs. OpenMV Cam will then determine the position, size, centroid, and orientation of each blob. Using colour tracking, the OpenMV device is programmed to track the soybeans on the belt, with colours set using the Threshold Editor.

**Colour classifier** - Although distinct colour variances between soybeans with different moisture content can be seen, preliminary results indicated that colour classification alone does not adequately describe the variations among different moisture content. NIR measurement is also needed.

**Thermal and NIR water content analysis** - The setup measures whole or cracked soybeans before drying, using infrared and NIR cameras. An infrared camera classifies soybeans at different moisture content levels using the thermal approach. The moisture content effects on the classification capability of colour, morphology, and textural features of imaged soybeans are evaluated. An NIR camera classifies soybeans at different moisture content levels using absorbance of water in the NIR spectrum.

The normal parameters measured on whole or cracked before drying and expanded soybeans flakes after drying are presented in Table 4.4.1 and Table 4.4.2, respectively..

**Table 4.4.1** Normal parameters measured on whole or cracked soybeans before drying.

Parameter	Value
Water content in soybeans	11,0 – 13,5 %
Oil content in soybeans	18,0 – 21,5 %
Accuracy of measure	+/- 0,2 %
Temperature in the soybeans	5 – 30 °C

**Table 4.4.2** Normal parameters measured on expanded soybean flakes after drying.

Parameter	Value
Target water content	9,5 %
Water content in soybeans	9,0 – 10,5 %
Oil content in soybeans	18,0 – 21,5 %
Accuracy of measure	+/- 0,2 %
Temperature in the soybeans	55 – 65 °C

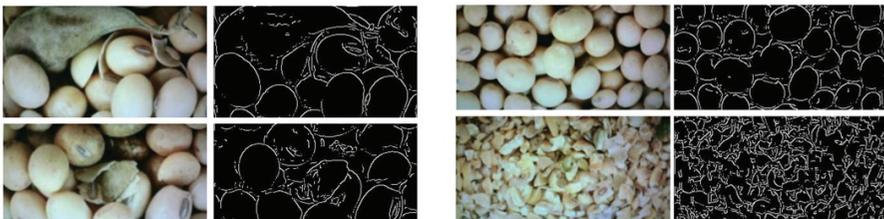
**Classification to detect variations on the production line** - A TensorFlow NN for image classification has been trained, optimised, and deployed on the OpenMV. A convolutional NN trained on the collected image data set for detecting soybeans is investigated. This approach can give robust results even with significant variations. CNN are exponentially more accurate and efficient than traditional computer processing models for AI use cases like recognition, identification, and classification tools.

The results of the machine vision functions applied on various soybeans samples are shown in Figure 4.4.7 and Figure 4.4.8.

The soybeans images processed by a binary image filter are presented in Figure 4.4.9.

#### 4.4.8 Summary and Future Work

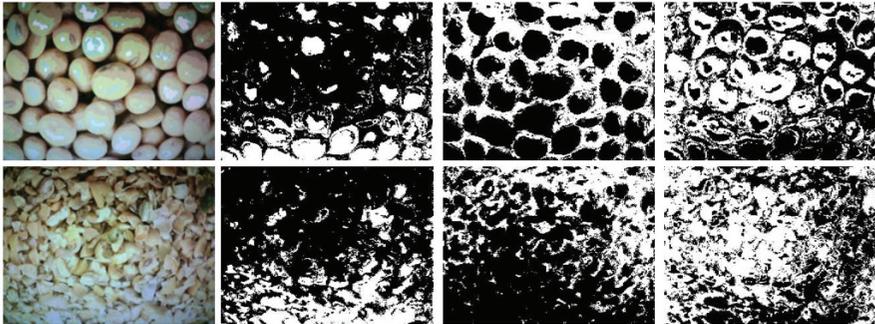
The soybean production flow is complex, and the many process steps of soybeans impact the quality of the derived products and energy consumption. These steps can be improved and optimised by monitoring morphological features, such as moisture, size, shape, texture, and colour in soybeans and using variations in these features to adjust in real-time.



**Figure 4.4.7** Boundary tracking for samples with impurities and split soybeans (left) and cleaned soybeans and crushed fractions (right).



**Figure 4.4.8** Image detection segmentation and processing for samples of cleaned soybeans (left), soybeans with impurities (middle) and crushed fractions (right).



**Figure 4.4.9** Soybeans images processed by a binary image filter.

This optimisation is made possible by employing RT-AIoT (a combination of AI technologies with sensing and machine vision IoT devices integrated into industrial infrastructure) to achieve more efficient real-time IIoT operations. With such an integration, human-machine interactions are improved, enhancing data management and analytics.

The system proposed for soybean process optimisation, based on RT-AIoT, includes a flexible machine vision embedded platform that displays results interactively into the IIoT system.

A broad spectrum of hardware architectures is available with various trade-offs to deploy machine vision IIoT devices at the edge. Several architectures are under evaluation concerning the suitability for different machine vision functions for the soybean optimisation process, such as boundary detection, colour tracking, thermal analysis, classification, and appropriateness for placement on the three edge levels.

Machine vision IIoT devices are used as image sensors, AI-based processing nodes and communication devices to run neural networks on images and transfer the information to the industrial process system.

The creation of the model, training and validation are performed using standard ML frameworks. The generated models can run on the microcontrollers if optimised in memory, processing, and power capabilities. It is a matter of balancing the goals of obtaining the most significant reduction in the size of the original code with a minor accuracy loss.

In preliminary results, it is assumed that by placing machine vision IIoT devices at different locations in the processing workflow (e.g., on the conveyor belt before cleaning, on the conveyor belt after cleaning and before weight, and after crackers before conditioning), better sensor and AI functionality can be obtained. In turn, an improvement in product quality and process efficiency can be achieved with such a procedure.

Preliminary experiments are being conducted on an experimental test bench, mainly on soybean samples, to sense temperature, moisture, colour, weight and volume. The following steps are envisaged to adopt the same AI functions for soybean bulk samples, validating the proposed machine vision IIoT system and further integrating it into the soybean industrial process. Another possible activity is identifying the optimal soybean moisture measurement method considering precision, ease of calibration, size, robustness, processing capabilities and cost. Thermal imaging for moisture detection in soybeans to increase production efficiency and reduce energy consumption is a challenging issue and will be explored in the next steps. The camera functions like a microbolometer, i.e. multiple heat-detecting sensors sensitive to infrared radiation from 700 nm to 1000 nm wavelength. By setting a maximum and minimum temperature range, the thermal camera can be programmed in the IDE to function as a sensor for seeing objects of a particular temperature. It is important to note that the camera does not really “see” moisture in soybeans; it can detect slight temperature differences and patterns that reveal the existence of water.

Finally, as the soybeans are moved in a bulk fashion on the conveyor belt, further work will focus on ensuring that the system is equipped with high-speed imaging cameras. Global shutter cameras, which are recording all image data simultaneously, are used to take pictures of soybeans on a conveyor belt. Preliminary simulations were performed with the OpenMV global shutter. Provided the exposure is short enough, the image has no motion blur on moving objects. However, the trend is to increase the exposure time to obtain more lighting on the camera and the best signal to noise ratio. The choice of the camera requires reaching a balance between increasing exposure time as much as possible (resulting in slightly higher levels of noise) and preserving the image accuracy, resolution and reliability, also allowing the algorithm to be programmed within the IDE.

## **Acknowledgements**

This work is conducted under the framework of the ECSEL AI4DI “Artificial Intelligence for Digitising Industry” project. The project has received funding from the ECSEL Joint Undertaking (JU) under grant agreement No 826060. The JU receives support from the European Union’s Horizon 2020 research and innovation programme and Germany, Austria, Czech Republic, Italy, Latvia, Belgium, Lithuania, France, Greece, Finland, Norway.

## **References**

- [1] Vermesan, O., and Bacquet, J. (2020). *Internet of Things – The Call of the Edge. Everything Intelligent Everywhere*. Gistrup: River Publishers. Available online at: <https://doi.org/10.13052/rp-9788770221955>
- [2] Vermesan, O., and Bacquet, J. (2018). *Next Generation Internet of Things - Distributed Intelligence at the Edge and Human Machine-to-Machine Cooperation*. Gistrup: River Publishers. Available online at: <https://doi.org/10.13052/rp-9788770220071>
- [3] ECSEL AI4DI project. *Artificial Intelligence for Digitising Industry*. Available online at: <https://ai4di.eu/>
- [4] Report on hybrid reference system level architecture design for the digitizing industry. AI4DI, D2.1, June 2020.
- [5] Microwave technology. *Moisture, dry substance and concentration - Microwave measurements, (Rev.02)*. Berthold Technologies GmbH & Co. October 2018.

- [6] Jusoh, M.A., Abbas, Z., Hassan, J. Azmi, BZ, and Ahmad, A.F. A Simple Procedure to Determine Complex Permittivity of Moist Materials Using Standard Commercial Coaxial Sensor. ResearchGate, Measurement Science Review ù April 2011.
- [7] Okamura, S. (2000). Microwave Technology for Moisture Measurement. *Subsurface Sensing Technologies and Applications*, 1, 205–227 <https://doi.org/10.1023/A:1010120826266>
- [8] Pandey, T., Bhuiya. T.K., Singh, R., Singh, B., Harsh, R. (2012). A Review on Microwave Based Moisture Measurement System for Granular Materials. *IOSR Journal of Electronics and Communication Engineering (IOSR-JECE)*, Volume 3, Issue 2 (Sep-Oct. 2012), 37-41.
- [9] Zambrano, M.V., Dutta, B., Mercer, D.G., MacLean, H.L., Touchie, M.F. (2019). Assessment of moisture content measurement methods of dried food products in small-scale operations in developing countries: A review. *Trends in Food Science & Technology*, Volume 88, 484-496. Available online at: <https://doi.org/10.1016/j.tifs.2019.04.006>
- [10] A. Kerr, H. Rafuse, G. Sparkes, J. Hinchey, and H. Sandeman. “Visible/Infrared spectroscopy (VIRS) as a research tool in economic geology: Background and pilot studies from Newfoundland and Labrador”. Newfoundland Department of Natural Resources, Geological Survey, Report 2011-1, pp. 145-167, 2011. Available online at: <https://www.gov.nl.ca/iet/files/mines-geoscience-publications-currentresearch-2011-kerrvirs-2011.pdf>
- [11] OpenMV. Available online at: <https://openmv.io/>
- [12] MPCam. Available online at: <https://www.siana-systems.com/mpcam>
- [13] STM32MP157F-DK2. Available online at: <https://www.st.com/en/evaluation-tools/stm32mp157f-dk2.html>
- [14] STM32H747I-DISCO(VERY). Available online at: <https://www.st.com/en/evaluation-tools/stm32h747i-disco.html>
- [15] Soybean seeds. (2009) Feedipedia. Available online at: <https://www.feedipedia.org/node/42>

