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## KNOWLEDGE MANAGEMENT FOR DATA ANALYTICS IN ADDITIVE MANUFACTURING

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## ABSTRACT

*As a multi-staged digital manufacturing process, Additive manufacturing (AM) inherently benefits from data analytics (DA) decision-making opportunities. The abundance of data associated with the various observations and measurements taken throughout the design-to-product transformation creates ample opportunities for iterative, process improvements. To best formulate and address these opportunities, knowledge needs to be strategically and deliberately managed for efficient DA development. However, knowledge in AM is broad and comparatively sparse, making it difficult to create robust DA solutions. Also, existing methods for knowledge management in AM are often case-dependent. To address such challenges, this paper proposes a novel framework to manage case-independent knowledge for AM data analytics. The proposed framework consists of two phases: a knowledge-identification phase and a knowledge-representation phase. A knowledge architecture is defined to provide a reference for discovering knowledge that facilitates AM data analytics. In the knowledge identification phase, the architecture is used to facilitate the identification of actionable knowledge relevant to a specific DA use case. In the knowledge representation phase, ontologies are used for representing and linking that identified knowledge. A case study of application scenarios demonstrates how actionable knowledge is identified, represented, and managed by the framework. The framework enhances efficiency of AM data analytics development and enables knowledge sharing, understanding and reuse in AM data analytics activities.*

Keywords: Data Analytics, Knowledge Management, Knowledge Representation, Knowledge Identification, Additive Manufacturing

## 1. INTRODUCTION

Additive manufacturing is an advanced manufacturing technology process that builds parts by adding layers on top of each other based on the existing 3D CAD model [1]. With accompanying sensors and equipment, AM processes can generate a massive amount of big data with great volume, variety, and velocity [2]. Accordingly, several, data analytics (DA) technologies can be applied to AM big data to improve AM decision-making [3]. The outputs can provide new opportunities for optimizing and controlling AM processes based on that knowledge [4].

Knowledge is critical to improving the DA performance [5], and as such is an important source for understanding the AM domain and analyzing the data. Acquiring that data and creating and utilizing new knowledge from it requires various resources including human experts and specialized software. They are both time-consuming and based on [6] non-value-added activities. Therefore, it is critical to have the ability to acquire, represent, manage, and store the various types of AM knowledge.

Knowledge in the AM domain is broad and complex, and managing such domain knowledge is a challenging task [7]. There is a lack of comprehensive and readily available knowledge for AM. These data-rich but knowledge-sparse features of AM, makes it more difficult to use that data to create and manage AM knowledge bases [9]. Although data analytics techniques have matured over time, there are only few published studies that concentrate on using them to develop AM knowledge bases [8]. Most of the existing studies address the knowledge needed for using DA to solve a specific, AM activity [9, 10]; but that knowledge cannot be applied to other AM activities.

This is because AM lacks standard practices for 1) handling data, 2) creating common information structures from that data, and 3) developing an AM knowledge base from that information [11]. Consequently, there are only a few, novel methods for deriving and managing the AM knowledge necessary to support specific, AM-related, data analytics tools. Even though AM data analytics opportunities with high importance and high feasibility are available [12], large knowledge gaps still exist on how to take advantage of them through DA development. Therefore, new methods are needed to effectively address these gaps and systematically manage the knowledge that is essential for using data analytics to improve AM process control.

In this paper, we introduce a novel knowledge management framework for AM data analytics. This framework identifies knowledge from AM data analytics use cases and represents knowledge that is essential for AM data analytics. The framework consists of two sequential phases: knowledge identification and knowledge representation. For the knowledge identification stage, we define a knowledge architecture for AM data analytics. The knowledge architecture is used to identify the knowledge of a specific, AM, data-analytics use case. In the knowledge representation stage, we define knowledge models to represent and link knowledge identified through the knowledge architecture.

Figure 1 shows a descriptive illustration of the knowledge management process, which is leveraged by our proposed framework. The figure shows how the framework is used in the knowledge management process for AM data analytics. In the process, knowledge from DA use cases are associated with the knowledge architecture. The knowledge outputs from each use case are represented using specific knowledge models. Finally, the knowledge representations of every use case are 'combined' to create a single knowledge representation – called "the global knowledge representation".

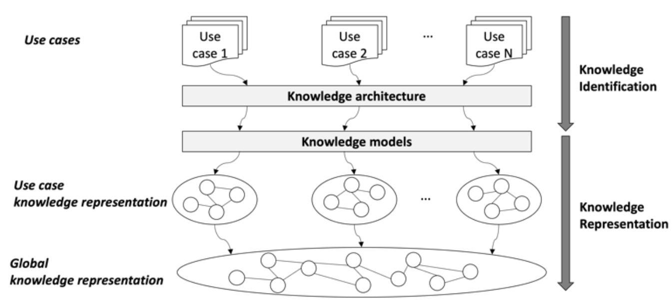


**FIGURE 1:** KNOWLEDGE MANAGEMENT PROCESS

The remainder of the paper is as follows. Section 2 describes the background of our proposed, ontology-based, knowledge representation and management in AM, AM data analytics (DA) tools, and knowledge architectures for using those tools. Section 3 introduces the proposed framework for knowledge management for AM data analytics. Section 4 demonstrates a case study of the proposed framework. Lastly, this paper is concluded with contributions and future work in Section 5.

## 2. BACKGROUND

### 2.1 Ontology in AM

An ontology is a common way to represent knowledge. An ontology is a set of concepts and categories in a domain that possesses the properties and relations between them. Ontologies are used for sharing a common understanding of the structure and content of information and reusing domain knowledge [13]. Ontologies have been applied in knowledge representation and management for their advanced capabilities that include knowledge sharing, processing, reusing, capturing, and communicating [14]. Such ontologies provide 1) sophisticated knowledge for a better understanding of the domain and 2) new opportunities for discovering new knowledge [15].

Ontologies have been used to create AM knowledge bases, and existing foundational ontologies such as basic formal ontology (BFO), common core ontology (CCO), and coordinated holistic alignment manufacturing process (CHAMP) are used for AM ontologies to increase the chances of reuse and integration with other ontologies [16]. Recently, ontologies have been used in AM applications for knowledge representation and management [17]. Related works have developed ontologies for representing and managing AM, process plans [18], AM process parameters [19], AM product lifecycle [19], and AM sensor data [20]. The most recent studies apply DA tools for developing ontology-based, knowledge representations. For instance, machine learning and knowledge graphs were used for constructing the design for AM (DfAM) ontology [21]. Also, ontologies are used for solving a specific DA task. In [9,10], the authors proposed DA-related knowledge management methods for solving specific AM activities. As of now, ontology-based representations for DA opportunities in AM have been generally limited to collaborative knowledge management [12].

### 2.2 Data analytics in AM

AM DA tools are used to optimize and control the AM design-to-product transformation process [11]. Advanced DA tools such as artificial intelligence (AI) use AM big data as an input to provide actionable knowledge [12]. Those DA tools are used throughout the entire AM product lifecycle. For example, they are used to make design feature recommendations, material predictions, build-time predictions, cost estimations, topology optimization, shape deviation predictions and AM powder classifications [11]. Using ontologies to represent knowledge enhances repeatability, fidelity, and functional integrity in developing and providing guidance for how to use AM data analytics [21].

Despite the continuing growth of applied DA in AM activities, there has been limited work on defining a common knowledge structure for implementing DA in AM. Additionally, according to [11], the knowledge that is created and used for implementing a specific DA tool is not well-managed. Managing the knowledge of AM data analytics use cases will lead to knowledge sharing, understanding and reuse in the process of developing AM data analytics.

 

## 2.3 Knowledge architecture for AM data analytics

A knowledge architecture for AM analytics is presented to support our proposed framework. The architecture is a schematic diagram of the knowledge that is required for developing a specific AM DA use case. The architecture is used to identify the knowledge needed for each such use case. The knowledge architecture, which is shown in Figure 3, is derived from the DA implementation process shown in Figure 2 (A). Figure 2 involves two processes: implementing a DA use case and identifying knowledge generated from that DA use case.

DA use cases are implemented in sequential steps, as shown in Figure 2 (A): domain understanding, data understanding, data preparation, DA development, and DA use case transition. The knowledge for developing DA is identified in the opposite direction to implementing DA use cases. Figure 2 (B) shows that knowledge for developing DA is identified in the order of use case knowledge, DA knowledge, data knowledge, and domain knowledge.

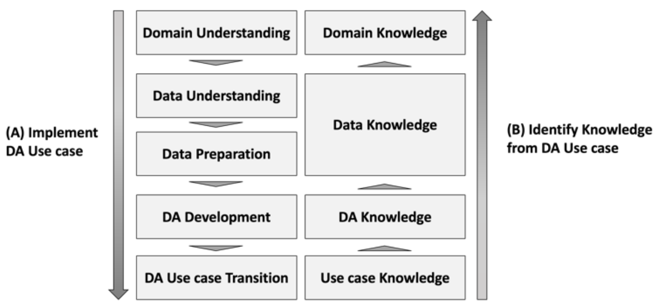


**FIGURE 2:** (A) DA IMPLEMENTATION PROCESS, (B) KNOWLEDGE IDENTIFICATION PROCESS

Use case knowledge can be identified by referring to the transitioned DA use case. DA knowledge is determined by the DA model created for the use case. Data knowledge is specified according to the data used for the DA model. Domain knowledge is identified by investigating how the data was transformed with the domain knowledge.

According to the process of knowledge identification, the knowledge architecture for AM data analytics is shown in Figure 3. The knowledge architecture describes key knowledge components that are required for implementing DA use cases in each step of knowledge identification. The knowledge architecture consists of use case knowledge, DA knowledge, data knowledge and domain knowledge.

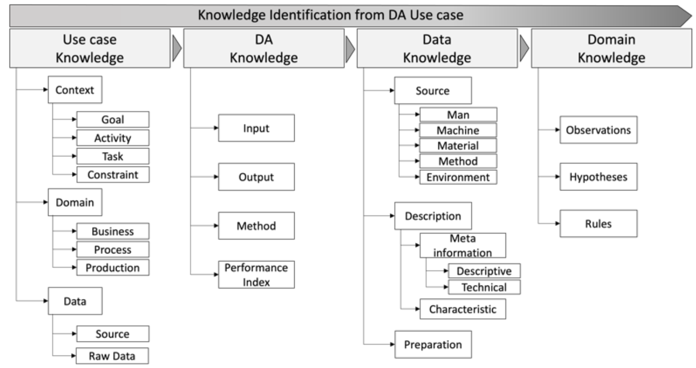


**FIGURE 3:** KNOWLEDGE ARCHITECTURE FOR AM DATA ANALYTICS

Use case knowledge describes the content of a use case by defining the AM problem that needs to be solved using DA, including the context, domain, and data associated with that use case. Context includes the goal, activity, DA task, and constraint components. Domain describes business, process, and production perspective of the use case. Data, which indicates the raw data, includes data source and description.

DA knowledge describes the functional components of the DA model, including the input, output, method, and performance index of the DA model applied in the use case. Data knowledge expresses knowledge needed to make the input data of the DA model, including data source, data description, and data preparation. The data source is explained with 4M+1E, indicating Man, Machine, Material, Method, and Environment [23]. The description is the meta information component that explains descriptive and technical contents of given data and the characteristic component that describes distinctive factors of the data. Domain knowledge helps understand the given data with observations, hypotheses, and rules explaining the data content from a domain perspective.

## 3. OUR PROPOSED FRAMEWORK

Our proposed framework uses multiple AM data analytics examples, so-called use cases, to identify the appropriate knowledge and to represent that identified knowledge for knowledge management. The framework consists of two phases: knowledge identification and knowledge representation.

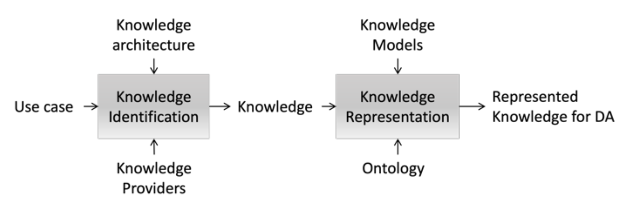


**FIGURE 4:** OVERVIEW OF KNOWLEDGE MANAGEMENT

Figure 4 shows an overview of our proposed framework. In phase 1, knowledge needed for developing DA is identified from DA use cases. The knowledge providers discover that knowledge based on the existing knowledge architecture. Knowledge architecture provided in Section 2.3 is used as a form to give directions to capture knowledge. In phase 2, the knowledge needed for developing DA is represented by developing knowledge models to the identified knowledge using an ontology. Here, ontology is used as a tool for creating knowledge models to represent knowledge. Details of each phase are explained below.

### 3.1 Phase 1 - Knowledge identification in AM data analytics

In the knowledge identification phase, knowledge providers discover knowledge from a use case (see Figure 2 (B)). First, use case knowledge is identified with its "*context*", "*domain*" and "*data*". "*Context*" is defined with a specific "*DA task*" with one or more "*constraints*", an "*activity*" supported by the DA task, and a "*goal*" of the activity. "*Domain*" is defined with a specific "*business*" area, "*process*" refers to the stage of the lifecycle, and "*production*" of the final product. "*Data*" indicates raw data that is used in the use case, described with the "*source*" of raw data and "*description*" of raw data.

Starting from the "*DA task*" in the "*context*" of use case knowledge, DA task knowledge is discovered with its "*input*", "*method*", "*output*" and, "*performance index*". "*Input*" describes the transformed data that is used as an input for the "*method*" of developing the "*DA task*". "*Method*" is a specific algorithm for modeling the "*DA task*". "*Output*" is the resulting model of the "*method*" and "*performance index*" is a measurement tool for assessing the performance of the "*method*".

To understand the "*input*" of a "*DA task*" for DA knowledge, data knowledge is discovered with "*source*", "*description*" and "*preparation*". "*Source*" of data includes each situation of "*man*", "*machine*", "*method*", and "*environment*", when data is collected. "*Description*" describes the data with "*meta information*" and "*characteristic*". "*Meta information*" consists of a "*descriptive*" part that illustrates the data and a "*technical*" part that explains specifications of the data from a data engineering perspective. "*Characteristic*" identifies distinctive properties of data that are used as a reference for data handling. "*Preparation*" describes the sequential steps of creating the final transformed data that is used for developing DA.

Domain knowledge is identified to understand the references for "*preparation*" of data knowledge. Domain knowledge is identified with "*observations*", "*hypotheses*", and "*rules*". "*Observations*" are defined with experience, facts, or measurement of the target domain. "*Hypotheses*" are assumed with tentative statements referring to "*observations*". "*Rules*" that are used as a reference for data preparation are determined using "*observations*" and "*hypotheses*".

### 3.2 Phase 2 - Knowledge representation in AM data analytics

Knowledge representations are developed for identified knowledge, in our case using an ontology, as shown in Figure 5. Four types of knowledge models can be developed: 1) a use case knowledge model, 2) a DA knowledge model, 3) a data knowledge model, and 4) a domain knowledge model. These four models link the four individual representations to one knowledge representation.

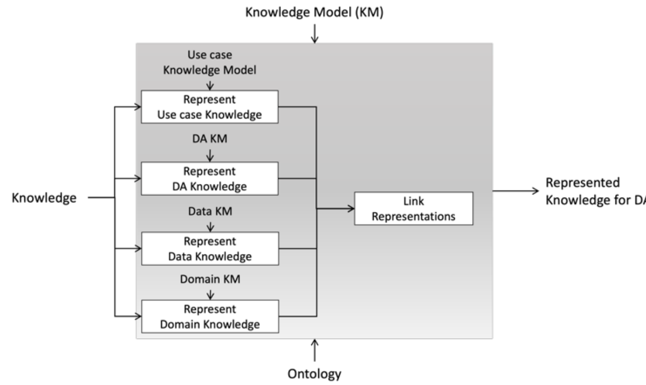


**FIGURE 5:** KNOWLEDGE REPRESENTATION OF A USE CASE

Ontology-based knowledge models represent knowledge with classes and properties. Classes describe sets or individual components of knowledge, and properties represent relations or attributes between classes. Figure 6 shows properties between high-level classes, for example, "*Domain knowledge influences data knowledge.*" and "*Data knowledge is used for DA knowledge.*". As shown in Figure 6, individual knowledge representations are linked to one knowledge representation by properties. Domain knowledge "*influences*" data knowledge, and data knowledge "*is used for*" DA knowledge. DA knowledge, domain knowledge, and data knowledge "*explain*" use case knowledge.

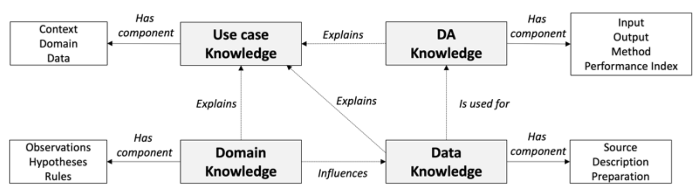


**FIGURE 6:** KNOWLEDGE REPRESENTATION USING ONTOLOGY-BASED KNOWLEDGE MODEL

Knowledge representation has classes according to the knowledge architecture and these classes are linked with the property "*has component*". Each knowledge model defines properties between classes to establish a scope of knowledge. For example, the use case knowledge model defines properties between classes of use case knowledge components. Details of the knowledge models are described in Table 1.

**TABLE 1:** DETAILS OF THE KNOWLEDGE MODELS

| Knowledge Model | Subject Class Information | | Property | Object Class Information | |
|---|---|---|---|---|---|
| | Parent | Subject | | Parent | Subject |
| Use case | Context | Constraint | *Restricts* | Context | Task |
| | Context | Task | *Supports* | Context | Activity |
| | Context | Activity | *Aims* | Context | Goal |
| | DA Knowledge | Output | *Explains* | Context | Task |

| | | | | | |
|---|---|---|---|---|---|
| | - | Domain Knowledge | *Explains* | Domain | Business |
| | - | Domain Knowledge | *Explains* | Domain | Process |
| | - | Domain Knowledge | *Explains* | Domain | Production |
| | Data | Raw data | *Collected from* | Data | Source |
| | - | Data Knowledge | *Explains* | Data | Raw data |
| | - | Data Knowledge | *Explains* | Data | Source |
| **DA** | DA Knowledge | Input | *Is used for* | DA Knowledge | Method |
| | DA Knowledge | Performance Index | *Measures* | DA Knowledge | Method |
| | DA Knowledge | Method | *Results* | DA Knowledge | Output |
| | DA Knowledge | Output | *Explains* | Use case Knowledge | Task |
| | - | Data Knowledge | *Is used for* | DA Knowledge | Input |
| **Data** | Description | Characteristic | *Influences* | Data Knowledge | Preparation |
| | Meta Information | Technical | *Influences* | Data Knowledge | Preparation |
| | - | Domain Knowledge | *Influences* | Data Knowledge | Preparation |
| **Domain** | Domain Knowledge | Observations | *Defines* | Domain Knowledge | Hypotheses |
| | Domain Knowledge | Hypotheses | *Defines* | Domain Knowledge | Rules |
| | Domain Knowledge | Observations | *Influences* | Data Knowledge | Preparation |
| | Domain Knowledge | Hypotheses | *Influences* | Data Knowledge | Preparation |
| | Domain Knowledge | Rules | *Influences* | Data Knowledge | Preparation |

For example, DA knowledge is represented as shown in Figure 7. "*DA knowledge*" has "*input*", "*output*", "*method*" and "*performance index*" components with the "*has components*" property. "*Data knowledge*" is linked with "*input*" by "*is used for*" property, that represents the details of input data. "*Input*" has "*is used for*" property for "*method*", that shows the input data is used for the DA method. "*Method*" is linked with "*performance index*" by the "*measures*" property, representing how the DA method is evaluated. Also, "*method*" is linked with "*output*" by the "*results*" property, explaining the DA model which is developed with the method. Lastly, "*output*" is linked with "*task*" class of "*use case knowledge*" using the "*explains*" property, representing the DA model implies the DA task.

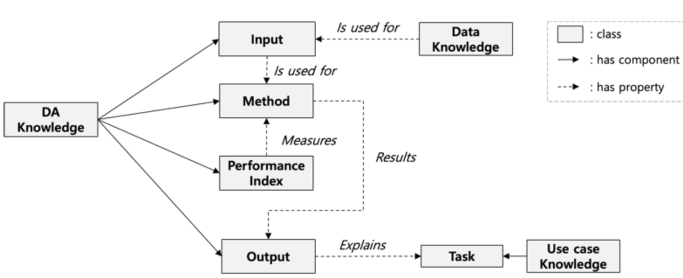


**FIGURE 7:** DA KNOWLEDGE REPRESENTATION

Figure 8 visualizes the overall knowledge representation via the VOWL package in protégé, which is an ontology tool [23]. The red box indicates the use case knowledge representation, the blue box indicates the DA knowledge representation, the orange box indicates the data knowledge representation, and the green box indicates the domain knowledge representation. Figure 8 shows how those four, different, knowledge representations can be linked to one knowledge representation by using those knowledge models.

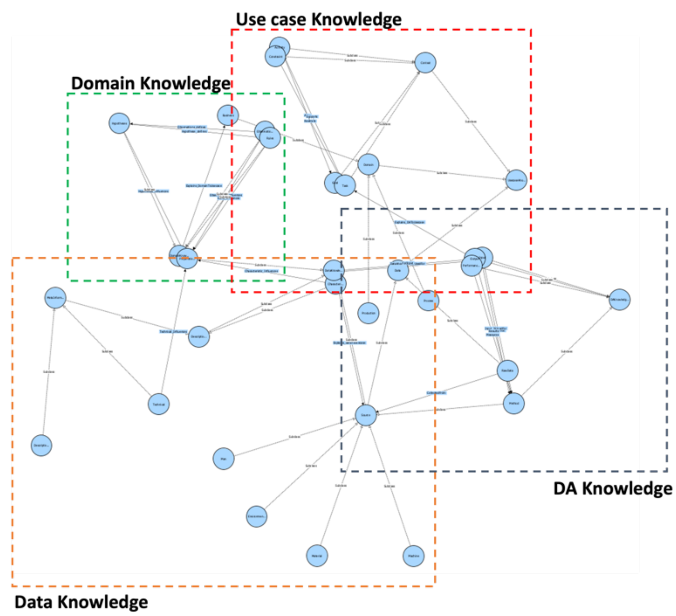


**FIGURE 8:** VISUALIZATION OF THE OVERALL KNOWLEDGE REPRESENTATION

## 4. CASE STUDY

In this section, the proposed framework is illustrated using "*melt pool size classification*" [24], as the target use case. Here, the input knowledge needed for the selected DA is identified from the target use case, using the knowledge architecture (Figure 3). Also, that knowledge is representated with ontology-based knowledge models.

In the knowledge identification process, each component of the knowledge architecture is discovered. Basically, this process starts with use case knowledge and goes through DA knowledge, data knowledge, and domain knowledge. First, use case knowledge is identified based on use case knowledge components, for example, "*context*" of the target use case is identified as "*melt pool size classification*" task with "*real-time*" constraints that supports "*process control*" activity to "*improve part quality*" goal.

To specify the "*task*" component of use case knowledge, DA knowledge is identified based on those same DA knowledge components. For example, "*melt pool size classification*" task is a "*classification model*" developed by applying "*CNN*" method with "*melt pool image, image label*" as an input.

To understand what the "*input*" component corresponds to, data knowledge is identified based on data knowledge components, for example, *"melt pool image data"* has technical meta information as "*type = image, size = 128*120 pixels, count = 2763*".

Finally, the "*preparation*" component of data knowledge is explained by identifying domain knowledge based on their related components. For example, a rule "*normal label area range = 0.11 ~ 0.014*" is based on a hypothesis "*normal label can be defined based on average hatch distance*". Table 2 shows the representative output of knowledge identification on the target use case.

**TABLE 2:** KNOWLEDGE IDENTIFICATION OF THE TARGET USE CASE

| **Knowledge Architecture** | | **Knowledge** |
|---|---|---|
| **Use case** | **Context – Goal** | Improve part quality |
| | **Context – Task** | Melt pool size classification |
| | **Context – Activity** | Process control |
| | **Context – Constraint** | Real-time |
| | **Domain** | AM, LPBF, In-situ monitoring |
| | **Data** | AMMT, Melt pool image |
| **DA** | **Input** | melt pool image, image label data |
| | **Output** | Classification Model |
| | **Method** | CNN |
| | **Performance Index** | • Accuracy = 91%<br>• Reaction time = 0.34 ms/images |
| **Data** | **Source** | • Machine: AMMT system, Galvo mirror system, beam splitter, high-speed camera triggered at every 500ms integration time of 20ms, heating laser, laser power P = 195W, scan speed = 800mm/s<br>• Method: serpentine scan strategy, FGA at 100 KHz<br>• Material: Inconel 625 powder, build plate, substrate dimension 102mm*102mm*12mm, part shape is a rectangle with chamfered corners with dimension 10mm*10mm*5mm |
| | **Description – Meta Information – Descriptive** | Image captured from laser melting powder fusion build |
| | **Description – Meta Information – Technical** | • Type: image<br>• Size: 128*120 pixels<br>• Count: 2763 |
| | **Description – Characteristic** | • The grayscale of the image is from 0 to 255<br>• Higher melt pool intensity correlates to a larger grayscale value |
| | **Preparation** | • Boundary detection<br>• Image labeling<br>• Resizing to 32*30 for computational efficiency |
| **Domain** | **Observation** | • Melt pool has irregular shapes<br>• Difficult measuring geometry<br>• Melt-pool geometry has width, length, deflection angles, tails, outline<br>• The boundary of a melt pool highlights the melt pool phase change frontier |
| | **Hypotheses** | • Melt-pool boundary is approximated with regular ellipse shape using least square fitting<br>• Melt-pool in same class can have different characteristics<br>• Boundary can be defined based on manual sketched boundary<br>• Normal label can be defined based on average hatch distance |
| | **Rules** | • Melt pool width: 2*minor radius<br>• Melt pool length: 2*major radius<br>• Melt poo area: area of the approximated ellipse<br>• Normal label area range: 0.011mm2 to 0.014 mm2 Boundary threshold: 150 |

In the knowledge representation process, identified knowledge of the target case is represented in classes, individuals, and properties using ontology-based knowledge models. This process begins with applying an existing, use case knowledge model to the newly identified use case knowledge. For examples, the "*context*" class consists of the "*goal*" class with an "*improve part quality*" individual; the "*activity*" class with a "*process control*" individual; the the "*task*" class with a "*melt pool size classification*" individual, and the "*constraint*" class with a "*real-time*" individual.

The DA knowledge is represented by applying an existing DA knowledge model to the identified DA knowledge. For example, the "*method*" class with a "*CNN*" individual and the "*output*" class with a "*classification model*" individual are both linked with the "*results*" property. Also, use case knowledge representation and DA knowledge representation are connected by linking the "*output*" class with a "*classification model*" individual and the "*task*" class with a "*melt pool size classification*" with the "*explains*" property.

The data knowledge model represents identified data knowledge, such as, the "*preparation*" class with "*boundary detection*" and "*image labeling*" individual. Moreover, the data knowledge model links data knowledge representation with both the use case knowledge representation and the DA knowledge representation. The "*data*" class in use case knowledge representation is linked with the "*data knowledge*" class by the "*explains*" property. DA knowledge representation and data knowledge representation are connected by linking the "*data knowledge*" class and the "*input*" class with "*is used for*" property.

Lastly, domain knowledge representation is implemented using the domain knowledge model, such as, the "*observations*" class with a "*melt pool has boundary*" individual. The domain knowledge model connects domain knowledge representation with use case knowledge representation and data representation. The "*domain*" class in use case knowledge representation is linked with the "*domain knowledge*" class with "*explains*" property and individuals of "*preparation*" class in data knowledge representation are linked with individuals in "*domain knowledge*" with "*influences*" property.

Figure 9 shows a portion of the knowledge representation of the target use case. Three application scenarios of the knowledge representation can be illustrated in the figure. First, we can understand the data preparation flow of the target use case. When we say $D_R$ in the figure, it means raw data; and we say $D_T$ in the figure, it means transformed data. We can discover how raw data gets transformed using our proposed, knowledge representation approach. Melt pool image data $D_R$ is transformed to $D_{T_1}$ and $D_{T_2}$ according to domain knowledge

 

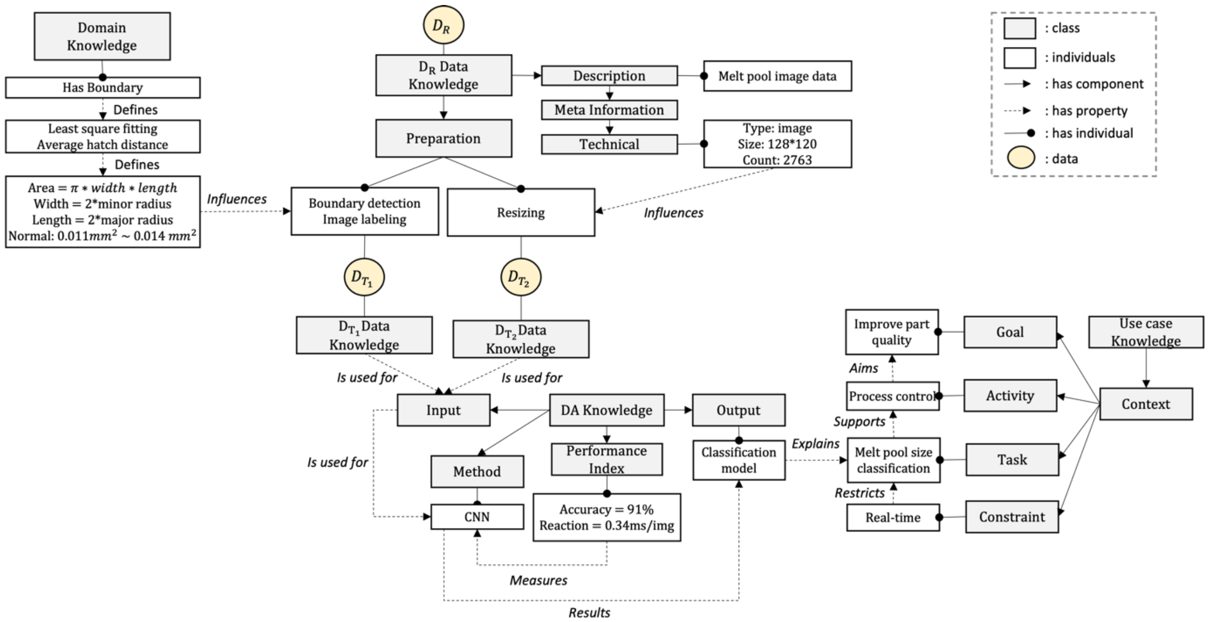


**FIGURE 9:** A PORTION OF THE KNOWLEDGE REPRESENTATION OF THE TARGET USE CASE

and data knowledge. In the process of generating $D_{T_1}$, domain knowledge is used for data preparation.

Domain knowledge explains the observation that melt pool has a boundary, and that observation defines two hypotheses that 1) the boundary is measured with least square fitting and 2) normal size is based on average hatch distance. The hypotheses then define two rules for data preparation: 1) computation function that measures area within the boundary and 2) the range of the normal, boundary-area size. Defined rules in domain knowledge are used for two, data preparation activities to generate $D_{T_1}$: 1) boundary detection and 2) image labeling. In the process of generating $D_{T_2}$, data knowledge is used for data preparation. Technical meta information, size of $D_R$, influences $D_R$ to be resized to $D_{T_2}$. Second, we can understand the overall DA description of the target use case. DA uses two transformed data $D_{T_1}$ and $D_{T_2}$ as inputs for training the CNN to develop a classification model. Also, we can see that the performance of the classification model is evaluated with accuracy and reaction time. Lastly, use case context can be described as a real-time melt pool classification task that supports process control to improve part quality.

The case study identified and represented knowledge to manage knowledge for developing the target use case "*melt pool size classification*". It is meaningful that we can manage actionable knowledge for DA through knowledge identification and knowledge representation. However, the case study did not link the representations of individual, use cases to implement global knowledge representation, and this is left for our future work. Also, evaluation method for validating the proposed framework should be considered in the future work.

## 5. CONCLUSION

In this paper, we proposed a novel knowledge management framework for AM data analytics. The proposed framework identifies knowledge using the knowledge architecture and represents knowledge with ontology-based knowledge models. In the case study, knowledge identification and knowledge representation were demonstrated with the target use case. Also, three application scenarios of the knowledge representation were illustrated to show that actionable knowledge for AM data analytics can be managed through the proposed framework.

This work enables knowledge sharing, understanding, and reuse in activities related to AM data analytics. Also, the proposed framework provides actionable knowledge for AM data analytics that contributes to reduce time and effort in developing an AM data analytics solution. In the future, we will focus on linking knowledge representations of use cases to create a global knowledge representation and further formalize the proposed framework.

## ACKNOWLEDGEMENTS

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