

Research article

Ontology-based Data Integration Framework for Smart Pig Farms

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Abstract

Semantic web technology is known to enhance data for the connection of information using a network that can be easily read by machines. This work applies an ontology to integrate data involved in swine farm management towards the development of smart farm for swine. To realize environmental data, IoT devices including sensors, camera, and RFID readers were deployed in a pig farm. Despite differences in data format from different sources, an ontology was crafted to provide semantic annotations that could unify the data and enhance them with tangible relationships based on the domain knowledge. The core concepts of this ontology were sensing data with temporal information and identifiable data to represent relationship between real-time environmental features and the pigs within the pen to improve pig management. The semantically enhanced data can thus be applied with semantic-based queries and inference reasoner. Smart services including monitoring, decision support, alerting, and automatic executing based on the deployed IoT devices are thus enabled to support farm managements towards smart farm for swine. From the results, we found that the integrated sensing information from sensors and knowledge given in the developed ontology with inference rules assists the task of interpretation of monitored information and decision-making to improve swine farm management. The data gathered could be extended by combining two or more factors such as temperature and humidity into heat index using knowledge inference to precisely understand environmental information and activate the relevant machine automatically.

Keywords: data integration; ontology; smart farm; pig farm; semantic annotation

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1. Introduction

The emergence of 5G technology for mobile internet and the significant increase of scale in cloud computing transforms our lives towards the concept of Smart Society, which uses digital technology, connected devices, digital networks for improving people's ordinary live. By forming a connection of wireless sensor networks capable of sensing, communicating, and computing, we can develop a smart home for improving quality of living and smart farm for better farm management and increasing yield potential. These wireless networks enable endless solutions including remote controlling, remote monitoring, and automated decision-making services.

Thailand is one of the major agricultural product providing countries that plans to apply the concept of Agriculture 5.0, which represents the future of the agricultural sector. The agriculture 5.0 emphasizes the adoption of advanced technologies for smart farming including the Internet of Things (IoT), artificial intelligence, and the utilization of big data to boost the efficiency of agricultural operations (Fraser & Campbell, 2019; Spanaki et al., 2021). Smart farming exploits such technologies to improve operations in agriculture and livestock farming by monitoring, analyzing, and controlling the production processes. This is especially true for smart farming for livestock, where the goal is to improve farmer ability to track individual animals as well as to provide for the needs of each animal. The application of these technologies can minimize the risk of health problems and improve overall herd health.

Technological progress in the field of IoT has opened the way for smart farming. A smart farm refers to a system that coordinates various farming activities based on real-time data collected and analyzed in context. Some existing work related to smart farming, for instance, Symeonaki et al. (2022) presented an architecture for a context-aware IoT middleware in IFM (integrated farm management) that utilizes cloud infrastructure and resources for efficient real-time remote monitoring and control of livestock facilities. Context-awareness allows for understanding the situation based on raw sensor data and offers customized intelligent services that meet the needs of end-users and the environment. The use of cloud computing resources also reduces the burden on sensing devices, provides centralized storage, and allows for information to be shared among all parties in flexible ways. A smart-farming ontology was created by Chukkapalli et al. (2020) to encode farm-specific sensors and interactions. They first established a smart farm ecosystem architecture that included physical entities, digital twins, and a representation graph. The farm equipment was classified, and various interactions between the owner, workers, sensors, and vehicles on the farm were thoroughly described.

Ngo et al. (2018) proposed a knowledge framework for an agriculture ontology aimed at smart agriculture systems. The ontology encompasses not only fundamental concepts in agriculture but also includes geographical data, IoT, business subdomains, and knowledge obtained from various datasets. This ontology allows users to easily comprehend the relationships between agricultural data gathered from multiple sources. Additionally, this ontology can be utilized with real-world datasets for storage as linked data and the application of data analytics methods. While most current research on agricultural ontologies concentrate on vocabulary and concept modeling within the domain, the study of Ngo et al. (2018) demonstrates that agricultural ontologies can also be used to monitor crop progress and analyze agricultural data. Fuentes et al. (2021) conducted a study to examine the advantages of using data analytics to improve dairy production. To aid in this investigation, a Valacta center of expertise dataset detailing the performance of dairy cows and farms in Eastern Canada was used. The team tackled the task of creating a domain

ontology, known as the dairy cattle performance ontology (DCPO), based on this data. The DCPO can be used to organize complex and diverse dairy data into a consistent framework that can easily incorporate external data. Additionally, the DCPO provides a shared language for both human stake-holders and automated knowledge management systems, and in the future, it may facilitate the explanation of predictions made by neural models.

From the reviews, IoT allows the recognition of actual data related to environmental features important to farm management while an ontology depicts knowledge related to correct and effective farm management. Combining the benefits of up-to-date data from IoT and knowledge management from an ontology helps to ensure farm success and reduce the risks for smart farm. The combination of the two thus enables several applications including data monitoring, smart decision-making via knowledge inference, and automation.

Over the past decade, pig production in Thailand has experienced significant growth, which has had numerous economic, health, and environmental impacts (Thanapongtharm et al., 2016). A trend in the pig industry in Thailand has gradually shifted from small farms to large farming enterprise. This shift has occurred in response to increasing local and foreign demand for pork and also in response to improve pork quality for sustainable and better prices (Charoensook et al., 2013). There are various smart farming technologies that can be applied in pig farming, including sensing and monitoring devices such as thermometers, pressure mats and force plates, microphones, image capturing cameras, and an animal identity checkers with an RFID (radio frequency identification) chip (Wang et al., 2022) for achieving automated operations. Moreover, operating a pig farm competitively does not only involve farm internal management; it also requires ready access to external swine market and disease spread data. Hence, the challenges of smart pig farming involve the complexity of data structure, the possible lack of heterogeneity of data sources, and the paucity of semantic information present in raw data, all of which make it difficult to effectively analyze and make use of the data. Therefore, the aim of this study was to identify the best practices for semantic data integration in smart pig farming and examine the role of ontologies in enabling the integration of big data.

2. Materials and Methods

The use of an ontology as a middle layer to collect data from heterogeneous sources including sensors and shared data from the internet was proposed. The ontology plays the role of a semantic integration layer to model required real-time heterogeneous data for swine farm management. Thus, the integration of data from these sources becomes a standard format allowed to be used with existing semantic technology services and tools. An overview of the framework architecture is illustrated in Figure. 1

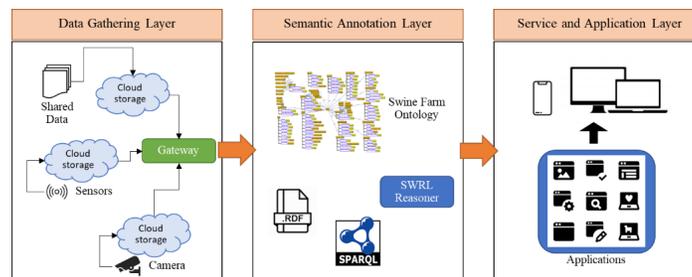


Figure 1. An architecture of the ontology-based data integration for smart pig farms

2.1 Data gathering layer

This layer is concerned with data required for management of the swine farm. For swine farm management, crucial information includes environmental information needed for monitoring and determining the proper habitat and environment for pigs to live comfortably, and other related information for farm planning such as farm-related financial information, and pork market price. In summary, we can group essential data into 8 aspects as described in Table 1. Each data however can be retrieved from several sources. For example, pig pen temperature can be measured with thermometer and recorded by an assigned respondent, or sensors can be deployed to continuously collect this data thus minimizing human error.

With several data sources, data are recorded in different formats based on the method of data collection. The sensing data from sensors (such as temperature in pig pen) should come with a recorded timestamp for referencing. The data retrieved from open data or public website (such as market price) should come with retrieving time for tracing back.

For best practice, a retrieving time for open data should be determined for specific timeframe of the day and the data should be updated daily for consistency. In the case of sensing data such as environmental aspects and weather aspects within a farm property, at least 5 records based on time with at a maximum of 5 h interval (such as in the morning, at noon, in the afternoon and evening, and late-night) are suggested for covering environmental changes in a day. In the case of a large pig pen or a pen with clear compartments, several sensors are recommended to cover all designated areas.

2.2 Semantic annotation layer (ontology for semantic schema of swine farm data)

As sensors from IoT encompass different systems and public data from different data sources, different terminologies are used to describe the same properties or object as well as various measurement ranges of deployed sensors. The variation in terminologies and measurement ranges may cause problems of heterogeneity management and interoperability in the farming management system. Thus, we need a technique to deal with the data meaning. An ontology represents a semantic schema where an entity represents a real-world object with the relations among objects based on the domain knowledge in a form of metadata (Gruber, 1995; Plirdpring & Ruangrajitpakorn, 2022), which is designed by domain experts. By using an ontology to represent data for the swine smart farm, the raw data can be annotated by semantic annotation using a predefined semantic model to unify its description and represent domain knowledge. As ontologies use formal definitions, they are generally defined as “tools for specifying the semantics of terminology system in a well-defined and unambiguous manner” (Gubbi et al., 2013), in the form of OWL language recommended by W3C (McGuinness & Harmelen, 2009). With OWL, semantic query and reasoning are available for inferring more insightful data from the raw data (Figure 2).

Based on the gathered data, an ontology that covers all aspects is designed to provide semantic relationships among the acquired data. The ontology was designed on Hozo ontology Editors (Kozaki et al., 2002) and based on ontology development guidelines (Mizoguchi, 2003; Noy & McGuinness, 2001). The designed ontology was composed and corrected by three experts. Two experts had a bachelor's degree in agricultural science and had at least 10 years of experience in pig farm management, while the third expert excelled in knowledge engineering and in particular in the creation of proper ontologies that included defining concepts, property relations and axioms. An overview of the graphical ontology schema is illustrated in Figure 2, and major ontological components are explained in Table 2.

Table 1. Data required for smart pig farm management and their suggested sources

Data Aspect	Definition	Sources	Note
Environmental sensors	Data on temperature, humidity, and ventilation in the pig pen	<ul style="list-style-type: none"> • Temperature sensor in a pig pen • Humidity sensor in a pig pen • Airflow sensor in a pig pen 	Several sensors in a pig pen are recommended.
Feed management	Data on feed consumption, feed conversion rate, and feed waste	<ul style="list-style-type: none"> • Feed weight • Feed conversion rate per meal • Left over feed weight 	-
Livestock monitoring	Data on the health, growth, and behavior of the pigs, such as weight, activity levels, and vital signs	<ul style="list-style-type: none"> • Daily Pig weight • Motion sensor • Vital sensor for each pig 	-
Production data.	Data on pig breeding, farrowing, and mortality rates.	<ul style="list-style-type: none"> • Breeding data • Mortality data 	-
Financial data	Data on costs, revenues, and profits	<ul style="list-style-type: none"> • Revenue data • Profit data • Transportation data • Farm management cost 	Weekly, monthly, and annually data are preferred.
Weather data.	Data on temperature, precipitation, and solar radiation	<ul style="list-style-type: none"> • Temperature sensor outside a pig pen • Humidity sensor outside a pig pen • Solar sensor outside a pig pen 	-
Market data	Data on pig prices, supply and demand, and market trends	<ul style="list-style-type: none"> • Pig local market price per kg. • Pork local market price per kg • Pig International market price per kg • Pork International market price per kg. 	Sharing data from reliable sources such as responsible government sector and authorized market
Labor data	Data on labor costs, productivity, and efficiency	<ul style="list-style-type: none"> • Hired labor salary • Owner salary • Shareholder dividend 	Weekly, monthly, and annually data are preferred.

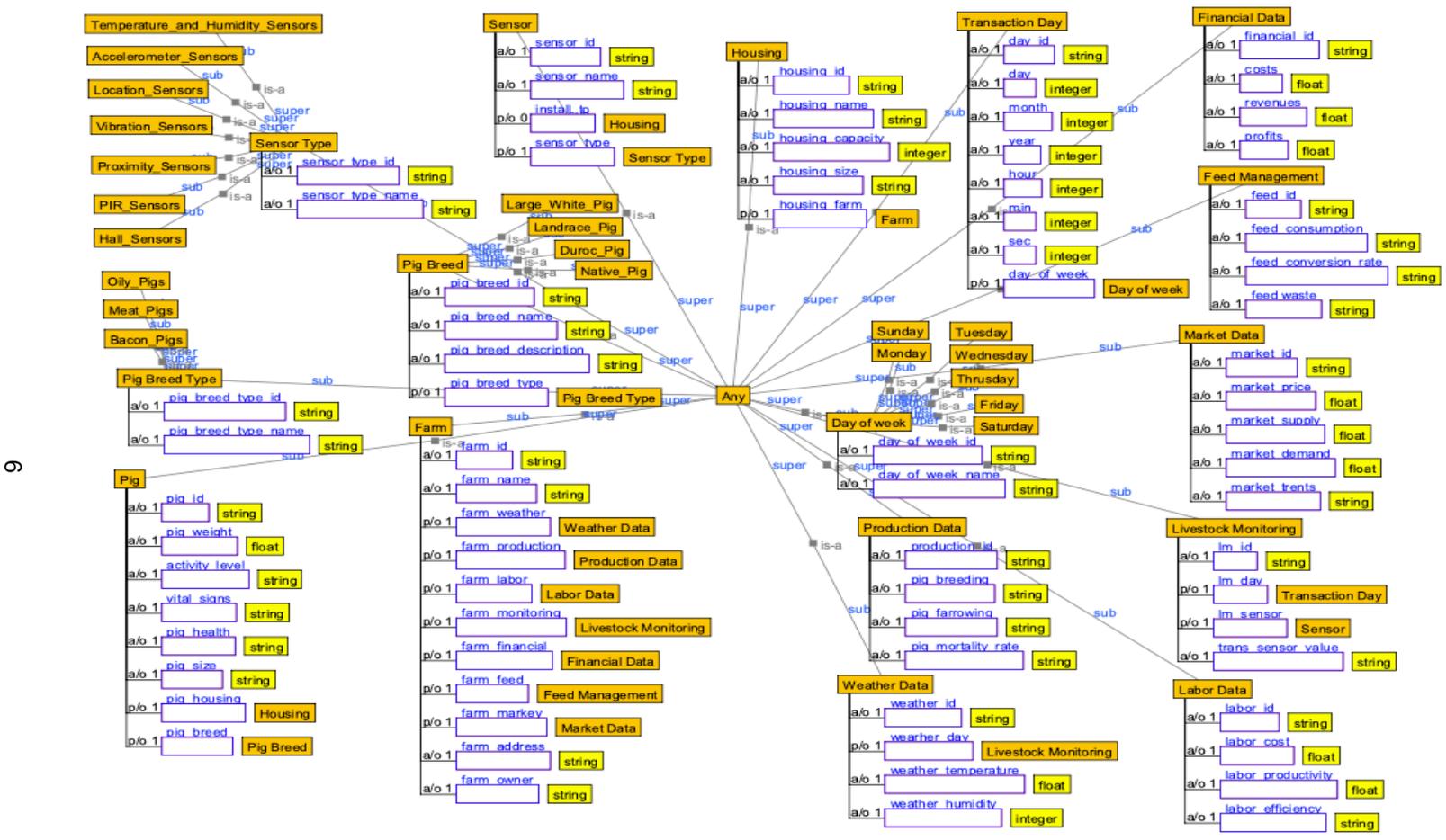


Figure 2. Graphical ontology schema for smart pig farm management

Table 2. Major ontological components and their relations

Ontology Component Name	Component Type	Relation to Other Components
Farm	Class (main tree)	p/o has_weather_data [Environmental_Data] p/o has_financial_data [Financial_Data] p/o has_weather_data [Weather_Data] p/o has_feeding_data [Feeding_Data] a/o has_owner [string] a/o has_farm_name [string]
Environmental_Data	class	p/o has_pig_pen [Housing] p/o has_sensor [Sensor]
Sensor	class	p/o has_sensor_type [Sensor_type] a/o has_sensing_value [float] a/o has_sensing_timestamp [datetimestamp]
Sensor type	class	sub Temperature_Sensor sub Humidity_Sensor sub Proximity_Sensor sub Weight_Sensor
Housing	class	p/o has_pig [Pig] a/o has_pig_pen_ID [string]
Pig	class	p/o is_pig_breed [Pig_Breed] a/o has_pig_ID [string] a/o has_pig_ID [string]
Pig_Breed	class	sub Oily_Pig sub Meat_Pig sub Bacon_Pig

Table 2 provides details of the designed ontology. For notations, 'p/o' stands for part-of property (object property) to connect a class to another class, while 'a/o' stands for attribute-of property (data property) to connect a class to data value. The range of both property types is given in brackets as another class for p/o and a data type for a/o. 'Sub' indicates the subclasses of the class, which are represented in a hierarchical tree structure. From the given information, we can connect classes semantically. From the given information, classes can be semantically connected, such as a farm being related to environmental data collected from sensors measuring temperature and humidity. With the designed ontology schema, these semantic annotations can be applied using semantic technologies, such as querying with SPARQL and inference-based reasoning for classifying and managing information.

2.3 Data mapping and instantiation

Data by themselves are meaningless and required to be processed into information to be useful in an application or service. In this part, we explain on how we manage the data instance to an ontological instance.

Prioritized instances in this work includes farm, pig pen, pig, financial data, and sensing data. An instance of a farm is to provide information regarding farm basic information including farm name, coordination, facilities within farm, and owner name. Pig

pen instances are for identifying pens in case of there are more than one pen in a farm while they also provide information on sensor setting in a pen including how many sensors, what type sensors are, and how many pigs are in the pen. Pig instances are to distinguish pigs in a farm to indicate their information based on given properties such as gender, birthdate, breed, health status, feeding rate, and growth rate. Instances of Sensor data are collected based on deployed sensors in both outdoor and indoor (closed pig pen).

The data can be generalized into 3 groups as common data, temporal data, and spatial data. For the first group, common data are such as farm name, pig breed, and consistent labor cost. These data can be assigned and mapped directly to their relatable ontological classes. The temporal data are data about time that related to sensing data collection. Sensor data consist of two parts which are the collect sensing value based on a sensor type and a timestamp referring to detecting time of the collected value. As there can be several same sensor types across the smart pig farm, data can be in high volume and confusable. Hence, it is preferable to for collected data to be identifiable. In this ontology schema, the collected sensing values must be coordinated with temporal data as a timestamp to identify time of collection and a sensor ID to identify sensor location. In case of a farm that has two or more pig pen in a different setting or environment features, spatial data should also be recorded and coordinated with other data for later use in applications since the data with more distinguishable informative features will benefit the query and reasoning process.

2.4 Services and application layer

With the help of semantic annotation, data are integrated under the same semantic structure, and applications can be designed to serve the need of farm management. We exemplify applications and services as use cases for managing smart pig farm.

- **Monitoring:** With the sensor data, farmers can remotely monitor the environment within the pig pen(s) from integrated sensing data as well as outdoor weather. The monitoring can help farmers to study relationships between environmental features and health issue that may affect growth rate and quality of the products. Furthermore, the monitoring data can help farmers to plan for possible additional cost and can be used as decision-supporting on future planning. The summarized data for monitoring can also be calculated and displayed in a dashboard for ease of use

- **Decision-supporting:** By using SPARQL to execute queries, farmers can access data in various aspects from past data collection. With ontological relations, semantic-based queries with forward chaining or backward chaining are available for looking through the implicit data. The data such as outside weather and changes in environmental features in the pig pen can be retrieved together to support planning to reduce future irrelevant cost as well as to improve quality of the products.

- **Alerting:** With reasoning available from semantic web technology, if-then production rules can be executed based on given criteria matching to the retrieved data. For instance, we can make a rule to alert when a temperature is unhealthy to the pig by giving a temperature threshold by using simple SWRL (semantic web rule language as follows:

```
[Temperature_sensor(?t) ^ has_sensor_value(?t, ?x) ^
swrlb:greaterThanOrEqual(?x, 33) -> alert(?hot)]
```

(lit: IF value from temperature sensor exceeds 33°Celsius, then system alerts for “heat problem occurs”).

With IoT devices, farmers may choose to remotely execute the device to solve the problem such as turning on a fan or increasing fan power to reduce the heat. This inference rules can be written in a simple UI without knowing SWRL syntax by using supporting tools such as ontology application management framework (Buranarach et al., 2016).

- **Automatic solution:** Combining monitoring and alerting can be used for developing a simple controlling over IoT devices. The inference results can be a command to execute the devices to solve issues remotely instead of just alerting. Depending on the deployed devices such as fan, feeding machine, misting, and sterilizer, issues such as improper environment in a pig pen can be automatically solved. Moreover, the rule can also be designed to handle a task including filling feeding bed based on preset timer or by detecting hungry behavior from the animal using camera.

The aforementioned services can be acquired from semantic technology combining with IoT. However, by applying machine learning approach, many more services can be deployed for smart farming to improve farm management such as illness detection from behavior or manifested physical symptom, market demand prediction to help on breeding planning, feed nutrition calculation, and so on

3. Results and Discussion

3.1 Demonstrative results

The static data (swine farm profiling information) and dynamic from sensors can be integrated into one schema. The collected and integrated data can be exemplified in Figure 3.

By collecting farm environmental data, the developed ontology can control the data in a uniformed structure. The semantic annotation from ontological relations can help for users to understand the farm information comfortably. From the examples in Figure 3, a user can monitor two pig pens for environment information including temperature and humidity with timestamp. The pig individuals in a pig pen can be traced for their static information such as gender, breed, and pregnancy status (for female pig) as well as their health information such as detected weight from a step-on weight sensor. From the example, its noticeable that ‘Pig_3’ has the unusual decreased weight, and a farmer can investigate the cause and take care on the pig before losing the pig. These integrated data can be used for smart service and application such as alerting service. As exemplified, both pig pens reach ‘hot’ temperature for 33.6 °C and 33.7 °C on 12:00:00, 3rd June 2021 (‘20210603T120000’) and the pig pen instance ‘House_2’ for 33.0 °C on 12:00:00, 4th June 2021 (‘20210604T120000’). With the alerting of ‘hot’ temperature, a farmer can manage and reduce the temperature by turning on fan to increase airflow.

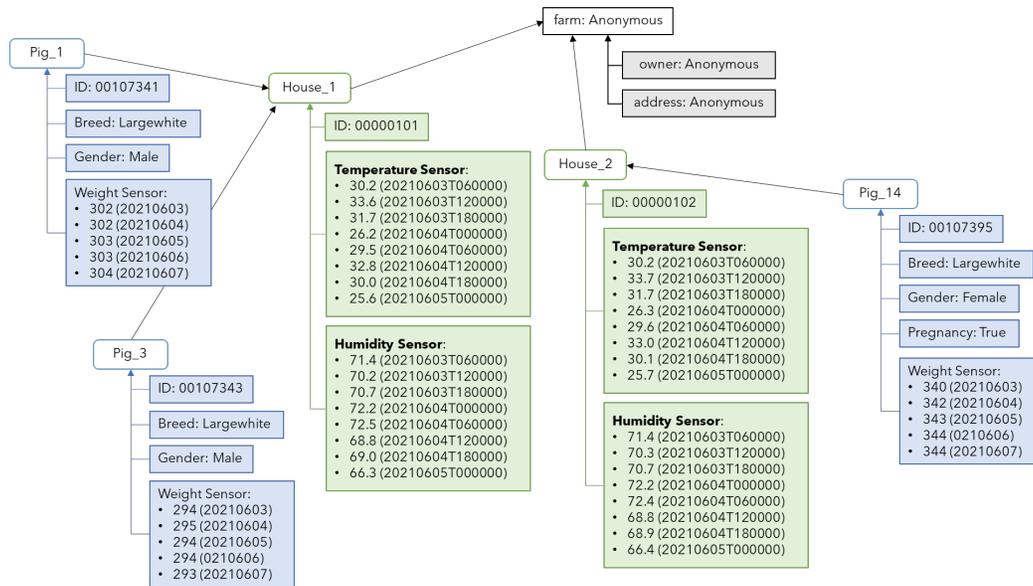


Figure 3. Graphical ontology schema for smart pig farm management

For the automation aspect, the prototype farm was equipped with a fan system and a dehumidifier system. The two systems were connected to the IoT for automated activation. With the ontological rules, the condition to activate the systems associates with the collected data by sensors and ontology schema. For the fan system, the condition to trigger the activation and deactivation is related to the inferred result of 'hot' from the inference rule of $[\text{Temperature_sensor}(?t) \wedge \text{has_sensor_value}(?t, ?x) \wedge \text{swrlb:greaterThanOrEqual}(?x, 33) \rightarrow \text{alert}(?hot)]$. Once the system is alerted with the 'hot' status, the fans will be automatically activated to reduce the temperature in the pig farm husbandry. The fans will be deactivated once the 'hot' status is off with 30 minutes delay. In a case of the dehumidifier system, humidity value is essential to pig health as the higher humidity, the higher chance the pig gets sick from fungal and bacterial diseases, especially pregnant pigs that may affect a birth rate and newborn weight from humidity stress (Tummaruk et al., 2010). To activate the dehumidifier system, the inference includes the different species of swine as their varied tolerance of humidity, pregnancy status of the pigs in the husbandry, and retrieved current humidity. For pregnant pigs in the specie of 'Large White' breed, humidity over 70% will trigger the dehumidifier to reduce the humidity in the husbandry to below 65%. This automation process thus helps farm owner to maintain best environment factors that may affect the farm success. However, it is still recommended for farmers to not neglect monitoring the pigs once received alerts as the automation may not cover all risk factors in raising pigs.

3.2 Usage results

In this section, we evaluate the operational efficiency and data management. For operational efficiency, we assess the time saved in some farming operations from automation and smart tools. The data management aspect involves evaluation of the quality of insights provided and how well the software supports decision-making. The

setting of this experiment is the observation of a volunteer swine farm in Ban Don, U-thong district, Suphan Buri province, Thailand. The pigpen of the farm was limitedly equipped (due to pig pen infrastructure) with the sensors including temperature sensors, and humidity sensors to capture environmental data. For responsive automation, two activatable fans and dehumidifier machines were deployed in the pen.

During the experiment period, we recorded the activation of fans in the pen based on the decision made by the system, and asked the farm caretakers if the activations were appropriate or not. We also asked the caretakers to note for when the tool should be activated but was not. The observed data were collected from 1st February 2024 to 31st March 2024. There were 76 times of fan activation, and 83 dehumidifier activation. The evaluation of the automation from the caretakers are given in Table 3.

Table 3. Evaluation of the decision-making

Activation Type	Activation time	Appropriate count	Missing count
Fan	76	76	6
Dehumidifier	83	75	1

From the results, we found that activations of fan were all appropriate based on assessment from the caretakers while 8 of dehumidifier activations were inappropriate (9.64%). There were also 6 and 2 times that the deployed fan and dehumidifier was not automatically activated although the farm caretakers thought they should be operated. From asking the reason and analysis, we found the followings.

Firstly, the missing of fan activations were from the time that the actual temperature did not exceed the given threshold, but the feels-like temperature may exceed the threshold. The actual temperature is the measure of how hot or cold the air is as recorded by a thermometer. However, the "feels-like" temperature referred to the apparent temperature which is an estimate of how the temperature actually feels to the living being body. It takes other various factors into account for human perception of temperature including Heat index and Sun exposure. High heat index from the combined effects of air temperature and humidity reduces the effectiveness of sweating in cooling the body leading to feel hotter than the actual temperature. Sun exposure can significantly increase the perceived temperature and make it feel warmer than the actual temperature especially when there is little to no wind. Thus, the caretakers decided that the fan should be activated at such time.

Secondly, the dehumidifier activations have both inappropriate count and missing of activations. All the inappropriate was because of raining at the time. As the pig pen is open-air, the caretakers decided that it is inappropriate to operate dehumidifier machines at the instances. For the single missing case, caretakers indicated that at the time the electricity was black out, and the sensors did not collect the data and activated the machine.

From the results, we conclude that the issues can be further solved by applying extra knowledge such as a concept of heat index and combining environmental factors for additional information. Furthermore, more sensor types should be deployed to accurately detect farm information. For the case of blackout, the system in practice requires a UPS (Uninterruptible Power Supply) to ensure the continuous operation of connected equipment by supplying power from stored energy.

4. Conclusions

This study demonstrates the effectiveness of integrating ontology-based data management with IoT technologies in smart pig farming, within the context of Agriculture 5.0. The deployment of sensors and automated systems significantly improved operational efficiency and decision-making on the farm. However, discrepancies in system performance, such as missed activations due to factors like heat index and rain, underscore the need for enhanced contextual awareness and additional sensor integration.

Future improvements should focus on incorporating more sophisticated environmental data and ensuring uninterrupted operation through power backup systems. Overall, the findings support the potential of smart farming to optimize agricultural practices and enhance farm management.

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6. Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper. All research was conducted impartially, and no financial or personal relationships influenced the outcomes or interpretations of this study.

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