PigSense: Structural Vibration-based Activity and Health Monitoring System for Pigs

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Precision Swine Farming has the potential to directly benefit swine health and industry profit by automatically monitoring the growth and health of pigs. We introduce the first system to use structural vibration to track animals and the first system for automated characterization of piglet group activities, including nursing, sleeping, and active times. PigSense uses physical knowledge of the structural vibration characteristics caused by pig-activity-induced load changes to recognize different behaviors of the sow and piglets. For our system to survive the harsh environment of the farrowing pen for three months, we designed simple, durable sensors for physical fault tolerance, then installed many of them, pooling their data to achieve algorithmic fault tolerance even when some do stop working. The key focus of this work was to create a robust system that can withstand challenging environments, has limited installation and maintenance requirements, and uses domain knowledge to precisely detect a variety of swine activities in noisy conditions while remaining flexible enough to adapt to future activities and applications. We provided an extensive analysis and evaluation of all-round swine activities and scenarios from our one-year field deployment across two pig farms in Thailand

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and the USA. To help assess the risk of crushing, farrowing sicknesses, and poor maternal behaviors, PigSense achieves an average of 97.8% and 94% for sow posture and motion monitoring, respectively, and an average of 96% and 71% for ingestion and excretion detection. To help farmers monitor piglet feeding, starvation, and illness, PigSense achieves an average of 87.7%, 89.4%, and 81.9% in predicting different levels of nursing, sleeping, and being active, respectively. In addition, we show that our monitoring of signal energy changes allows the prediction of farrowing in advance, as well as status tracking during the farrowing process and on the occasion of farrowing issues. Furthermore, PigSense also predicts the daily pattern and weight gain in the lactation cycle with 89% accuracy, a metric that can be used to monitor the piglets' growth progress over the lactation cycle.

CCS Concepts: • **Applied computing** → **Agriculture**; • **Hardware** → **System-level fault tolerance;**

Additional Key Words and Phrases: Swine, pig health, structural vibration, animal welfare, agriculture, precision management

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1 INTRODUCTION

Precision Swine Farming has the potential to directly benefit swine health and industry profit by automatically monitoring the growth and health of pigs. Implementing automatic monitoring throughout the high-risk farrowing and lactation periods especially can prove instrumental to pig farmers who wish to reduce risk and better protect their livestock. Reducing livestock mortality in the pork industry thus benefits not only the pig farmers, but also sellers and consumers of pork all over the world. Pork is one of the most popular meat products in the world and a huge worldwide industry. In 2019, 120 million tons of pork were consumed worldwide, compared to 69 tons of beef and 122 tons of chicken [30]. In pig production, farrowing mortality, lactation mortality, and vitality of the piglets are major economic and animal welfare issues for farm owners. Currently, the average lactation mortality in the US swine industry is nearly 18% [79]. Illness, piglet size, and parent-induced injury all contribute to this issue [4, 9]. Thus, monitoring during the lactation period is especially crucial, as it can allow caregivers to intervene in a timely manner to potential risks. Traditional monitoring relies on farmers manually observing sows and piglets, which is costly, time-consuming, and unreliable. In addition, manually handling the piglets to weigh them causes stress and may expose them to health risks [73].

Prior work takes a number of approaches, including using video or image analysis, motion detection, or wearable sensors on the pigs. However, these approaches may come with severe drawbacks when applied in the production farming environment. For example, image- and video-based approaches can monitor whole farrowing pens at once, but at the cost of large bandwidth, storage, and data processing requirements [13, 16, 44, 50, 65, 94]. In many cases, these processing requirements lead to delays in communicating crucial health information, because it only becomes available to farmers when the data can be retrieved and processed, often after weaning is over and the information is no longer relevant. In addition, video-based systems require a lighted area, which at night could disrupt the pigs' circadian rhythms, causing stress and harming the piglets [34]. Motion detection has been used to identify whether or not animals are active, but often fails to identify subtler behaviors such as nursing [25]. Wearable sensors can solve these problems, but face challenges with cost, application on the animals, battery life, and data transfer challenges that hamper true scalability [28, 36, 52, 75].

PigSense is the first system to use structural vibration to monitor animal behavior. It is non-intrusive to the animals and requires much less processing and storage power than non-vibration-based monitoring systems such as audio- or video-based systems. Our approach relies on the idea that animal activity creates unique vibration patterns in the structure of holding pens [10, 20]. For example, when pigs walk, their footsteps create vibration in the pen structure. When they lie down, their weight changes the natural vibration of the structure. By sensing this vibration, we can infer the different activities of the animals. We use geophone-based sensors attached to the floor of a farrowing pen to sense the structural vibrations generated by different animal activities.

PigSense monitors the farrowing (birth) and lactation period, focusing on activity detection that relates to piglet survival. Each farrowing pen that we monitor contains a single sow (a mother pig) and several piglets. When a sow is ready to give birth, she is moved to an individual farrowing pen, where she remains and nurses her piglets for three to four weeks. Both the farrowing process and the ensuing lactation period carry risks for the piglets. During farrowing, these include suffocation (which can occur during a long birth or when trapped in birth fluids after birth), hypothermia, accidental crushing by the sow, and even savaging by the sow [31]. Studies show that monitoring the farrowing process can halve piglet mortality rate during this time [41]. However, there is currently no automatic farrowing detection process in commercial pig farming [64]. As commercial farms grow, manually monitoring all sows becomes less feasible, necessitating a lower maintenance automated process such as the one we introduce in this article. By tracking the sow's innate pre-nesting behaviors before birth, our structural vibration sensors can predict farrowing the day before it begins. After birth, monitoring can detect symptoms of sow health status information such as sickness or lameness, as well as maternal behaviors that affect her capability to care for her newborns [52, 53, 61, 87]. In Section 4, we discuss how the structural vibration signal can be used to detect farrowing onset or sickness in the pens. In Section 5, we show how *PigSense* detects sow posture changes with up to 98% accuracy, which can reveal lameness or risk of piglet crushing, as well as ingestion activities that are linked to sow health. In addition to sow monitoring, *PigSense* directly monitors the piglet litter by detecting piglet nursing, active, and quiet periods in each farrowing pen. Changes in these metrics can alert farmers to possible sickness in the piglets. *PigSense* also gives a pen-level metric of piglet growth that can be used to help farmers determine if a pen is progressing normally without exposing them to the stress of manual handling and weighing.

Challenges. The key focus of this work was to create a robust system that can withstand challenging environments, has limited installation and maintenance requirements, and uses domain knowledge to precisely detect a variety of swine activities in noisy conditions while remaining flexible enough to adapt to future activities and applications. With this in mind, we address three major challenges:

1. Environmental Damage and Inconsistent Noise. Our first key challenge was withstanding the unpredictable environmental noise and possible hardware malfunction we encountered in the deployment environment. To cope with the challenging environment of an operational pig farm, our system prioritizes two types of fault tolerance:

Physical fault tolerance describes the robustness of our hardware system to *environmental damage*. Over several iterations of our hardware, we improve its robustness to individual node failures and increase physical node protection to prevent those failures. To achieve this robustness, we also focus on simplifying our inexpensive sensor nodes, allowing us to have multiple nodes that we can use as backups.

Algorithmic fault tolerance describes the robustness of our algorithms in sensing unreliability due to the deployment environment. This can be caused by inconsistent noise from temporary environmental changes (e.g., vibration from a sow urinating on a sensor) or differences in the structural response because the sow is lying in a different area of the pen. We also found inconsistencies in different sensors' data distributions due to unavoidable differences in their installation (e.g., sensor tilt, placement on the farm floor, or damping due to the attachment method of the sensor). To address these inconsistencies in the sensing nodes, *PigSense* performs individual analysis on each sensor before combining the results.

2. Limited Site Visitation. Our second challenge resulted from deploying our system in a new farming environment during a global pandemic, which necessitated the design of a system that could easily be installed by remote technicians without the oversight of the design engineers and tested remotely. **Deployability** describes the simplicity and replicability of the process used to set up the initial sensor system and maintain it at the farm. Our deployments were impacted by both human and swine global pandemics, which affected our ability to send researchers to the farm. In our first deployment, farm visitation became severely restricted after the sensors had been installed to protect the pigs from nearby outbreaks of African Swine Fever, which has posed a devastating threat to the global pork industry [19]. In our second deployment, visitation was restricted due to the novel human coronavirus. Therefore, it has been crucial to design systems that can be deployed and physically maintained by locals who may not be part of the system design team. Good *deployability* has the benefit of making our system more accessible and easier to maintain even without the added challenge of visitation restriction.

3. General vs. Task-specific Features. Finally, our system faces the challenge of distinguishing several behaviors that may happen concurrently, cause very similar structural vibrations to each other, or rarely occur in the data. During our analysis, *PigSense* uses domain knowledge of swine behavior and its effect on structural vibration to select features that are linked to the behaviors of interest and thus less likely to be a result of sensor deployment variation or environmental noise. This comes with a **tradeoff of feature generalizability vs. precision** during feature extraction and selection. We can be most precise in identifying certain pig behaviors by limiting our algorithm to recognize feature clusters that map specifically to those behaviors; however, doing so may cause our system to miss additional pig behaviors we had not previously accommodated in the system and also makes our system less versatile for adapting to non-pig-related environments. A careful balance of this tradeoff allows our system to adapt to new environments and new monitoring applications while still leveraging current domain knowledge to achieve precise results in noisy and challenging environments.

Contributions. To address these challenges, this work provides the following contributions:

(1) The first system that uses structural vibration to sense animal activity, to the best of our knowledge.
(2) Our experiences developing a failure-tolerant hardware and installation setup that is robust to environmental hazards, reproducible, and simple to deploy.
(3) An extended analysis of the relationship between structural vibration and various swine activities, with one-year test data from multiple farms, along with a discussion of the tradeoff between developing task-specific features based on physical and behavioral domain knowledge and extracting more general features that are able to accomplish various tasks.

We deployed our system at two operating pig farms: a commercial pig farm in Lopburi, Thailand, and the U.S. Meat Animal Research Center in Clay Center, Nebraska, United States. A total of eight farrowing/lactating sows and litters were used in the studies, with data from a minimum of three days before farrowing to approximately 25 days post-farrow.

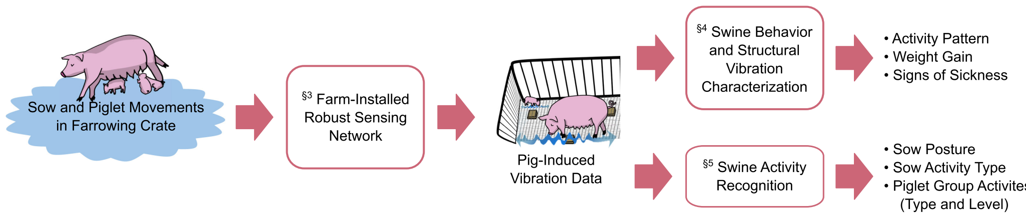

Fig. 1. A system diagram of *PigSense*. The system consists of three modules. The first module aims to acquire the vibration data induced by pigs. The second and third modules extract features from the vibration data to characterize the pig behavior patterns and infer their activity types and levels.

The rest of this article is organized as follows: Section 2 provides an overview of our *PigSense* system. Then, we dive into the details of each module in the system. Section 3 presents the design of our data acquisition system to maximize *physical fault tolerance* and *deployability*. Section 4 introduces how to characterize pig behaviors through the general features extracted from the vibration data. Section 5 describes the entire recognition system to detect and classify various sow and piglet activities. After that, we evaluate this system on two different long-term deployments on operational pig farms and discuss the results in Section 6. In Section 7, we review the related work, and finally, in Section 9, we conclude our work.

2 *PIGSENSE* SYSTEM OVERVIEW

This section presents an overview of the *PigSense* system. As shown in Figure 1, *PigSense* consists of three modules, including (1) a farm-installed robust sensing network, (2) the characterization of pig behavior and growth trends, and (3) sow and piglet activity and posture recognition.

The first module aims to acquire pig-induced vibration data using sensors attached underneath the farrowing pen flooring. The goal for the hardware and installation process is to maximize *physical fault tolerance* and *deployability*, which will be discussed in detail in Section 3. After capturing the vibration data induced by pigs, the second and third modules aim to understand the activity patterns and recognize certain activities through both *general and task-specific features* extracted from that data. Specifically, the objective of the second module is to characterize the swine behavior patterns through general features extracted from the vibration data (e.g., signal energy) and assess how different types of general features can be used to spot patterns in the data (see Section 4). In the third module, we describe the process of recognizing a comprehensive list of activities for both the sow and the piglets and discuss the tradeoffs we made in deciding when to use task-specific features to supplement the previously described general features (see Section 5). The system's output consists of the pigs' general behavior patterns (including the weekly/daily patterns, weight gain, and signs of sickness), the sow and piglet activity types, and their intensity levels.

3 FARM-INSTALLED ROBUST SENSING NETWORK

This section introduces the sensing network for data acquisition. Our sensing network consists of three tiers, as shown in Figure 2. The independent vibration sensors (Section 3.1) acquire the vibration signal via geophones while affixed to the underside of the pen. We incorporate protective hardware and high sensor redundancy to maximize *physical fault tolerance*. The centralized aggregator (Section 3.2) collects data from all of the sensors, storing and managing the flow of data both within the sensor network and off-site where the processing occurs. Performing data analysis away from the farm as described in Section 3.3 improves overall *fault tolerance* by separating

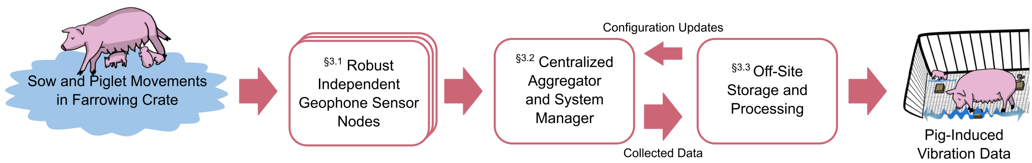

Fig. 2. A diagram of the *PigSense* sensing network. The tiered network design is shown, with the least reliable and lowest-powered devices to the left.

the demands of environmental resilience and computation power into different network tiers. The data output from this network is next analyzed using the methods described in Sections 4 and 5.

We found that the unpredictable and messy farm environment created our greatest reliability challenge when collecting the sensor data. This tiered model enables the desired *fault tolerance* by separating the tradeoffs of robustness, sensitivity, and adaptability. For example, we simplify the individual nodes that are exposed to the harsh environment in and beneath the farrowing pen. This simplification enhances the robustness of the individual nodes as described in Section 3.1 but makes them less able to adapt on their own. Their sensitivity and adaptation are then handled via reconfiguration from higher tiers. Device simplicity also contributes to *deployability* by reducing the complexity necessary for installation.

3.1 Independent Geophone Sensor Nodes

Our sensing nodes rely on geophone sensors [78] to detect the structural vibrations described in Section 4.1. Geophone sensitivity to subtle motion falls within our target sensing range (10^{-4} to 10^{-3} m/s). Geophone sensors have many advantages in a smart farming scenario. As described later in this section, they detect both movements and position changes of the pigs, including small movements such as piglet head bobbing that occurs with nursing, which a camera may not easily detect, since piglets are very small and often obscured by the sow.

The independent sensor nodes are individually robust and simple by design. Because they use components with low processing power, they can restart quickly and without intervention after errors such as temporary power loss, signal degradation, overflowing buffers, and minor node damage (e.g., water ingress). Additionally, we can place several within each pen for redundancy, while utilizing all nodes for recognition when available. Their robustness also contributes to *deployability* by mitigating potential failures due to improper installation.

Using geophone sensors as opposed to other sensing modalities also enables the *algorithmic fault tolerance* performed by the other modules. Because structural vibration responses are typically in lower frequency ranges, the geophones can be sampled much more slowly than the standard 8–16 kHz of a microphone, producing less raw data. This allows us to have redundant sensors and to upload data off-site for processing without being limited by low bandwidth or unreliable data connections, which are common in remote farm environments.

3.2 Data Aggregator and System Manager

The aggregator module interfaces between the individual sensors and the off-site storage and processing resources where most of the analysis is performed. We form the sensing network from a **single-board computer (SBC)** connected to a commodity wireless router, as shown in Figure 3. Each of the individual sensor nodes connects over WiFi to the router and communicates with the SBC using MQTT, a lightweight machine-to-machine networking protocol. Wireless links are used to avoid communication wiring, which is more sensitive to noise and hazards, from the farrowing area. MQTT requires only a small code footprint and very little processing and network overhead

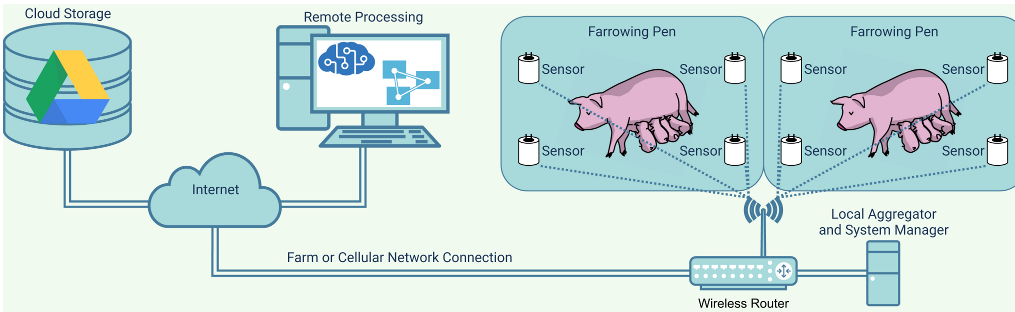

Fig. 3. A network map for *PigSense* showing the connectivity between the physical components.

to transmit the captured data [8]. The SBC aggregates data from all of the sensors in addition to providing system management and off-site upload capabilities.

Our network is configured in a simple star topology, as shown in Figure 3, but could be easily reconfigured for better scalability. We estimate that up to 50 sensor nodes can be adequately served before more complex network topologies will be necessary. The limiting factor in this case is the bandwidth to record sensor data to a single storage drive. Note that with higher sensor counts, efficient streaming data compression may be needed to accommodate the bandwidth constraints in a farm environment.

3.2.1 Manageability Tradeoffs. Once installed, the *PigSense* system is physically inaccessible as long as the instrumented pens are occupied due to the sensors' location below the pen. Therefore, any configuration or software updates must be performed remotely using the wireless link for data transmission. The ability for remote management enables greater *fault tolerance* and *deployability* for local workers who will have access to remote specialist support and system configuration.

Configuration and software updates require a tradeoff between system stability and adaptability. Allowing for updates inherently costs some stability, since it allows changes during the operation of the sensor network. Additionally, the communication channel for these updates is often unreliable because of the remote nature of pig farms, which tend to have unpredictable Wi-Fi and suffer from occasional power outages. This introduces the risk of partial or corrupted updates that could lead to a "bricked" condition where individual sensors can no longer communicate with the system manager. However, the benefit of updates comes in system adaptability. Updateable sensor software enables faster prototyping, since bugs can be fixed on the fly as needed. Configurability enables system adjustment based on unknown and changing environmental and installation conditions of, for example, sensor gain and sample rate. The tradeoff exists in balancing the competing priorities of time to deployment, environmental adaptation, and probability of sensor failure.

We combine our engineering and management policies to balance the competing interests of system reliability and robustness. Knowing that our communication channel is unreliable, we include software-based safeguards to ensure that remotely transmitted changes are valid before applying them. This is especially crucial with software updates, which could lead to a loss of connection with a given sensor. Policy controls such as restricting configuration changes to times when the pens are empty augment these safeguards. This restriction allows sensors that fail during updates to be replaced before the pens are again occupied.

3.3 Off-site Storage and Processing

Storing and analyzing data off-site improves the robustness of the system along all three of our primary metrics. It improves the *physical fault tolerance* of the system by simply avoiding the hazards

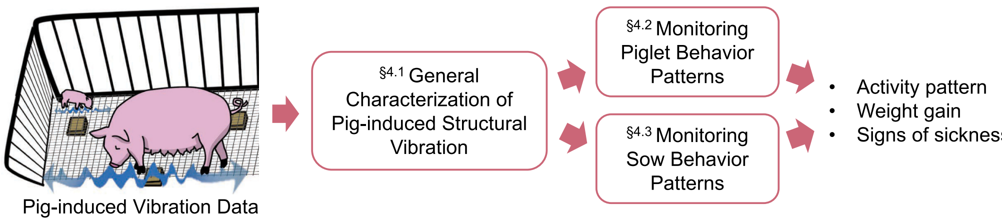

Fig. 4. A diagram for sow and piglet behavior characterization through structural vibrations induced by their behaviors.

of the farm environment such as water, animal excrement, and interference from the pigs. While liquid ingress is a common hazard in many environments, in the pig farm the acidity of animal urine leads to degradation of the seals that could otherwise protect the sensor electronics. Since these hazards make up the main source of failures, isolating our complex, high-computation resources in a different location handily bypasses these potential failures. The system then achieves *algorithmic fault tolerance* using analysis techniques that combine data from multiple sensors, weighing them based on reliability and the individual sensing task. Because of its complexity, this analysis would be more difficult to implement on-site. Finally, by reducing the number of complex devices required at the farm, off-site storage improves *deployability* within farms.

4 SWINE BEHAVIOR AND STRUCTURAL VIBRATION CHARACTERIZATION

In this section, we use the data collected through the sensing system to characterize swine behavior and its effect on structural vibration. As shown in Figure 4, we first characterize the vibrations induced by swine behaviors and discuss the features extracted (Section 4.1). Then, we demonstrate how the structural vibration response can be used to analyze hourly, daily, and weekly patterns in sow and piglet behavior in Sections 4.2 and 4.3. Finally, in 4.3.3, we show that deviation from expected behavior patterns can signify sickness in the pigs.

4.1 General Characterization of Pig-induced Structural Vibration

When a pig steps or lays down in its pen, its interaction with the structure induces the structure to vibrate. When a mature pig (approximately 300 kg [46]) stands versus lies on the structure, the load on the structure changes significantly. When the pig stands or steps, the load can be modeled as a point load, whereas when the pig is lying down, the load can be modeled as a uniformly distributed load. This alters the structural vibration response under the same support condition. In a 2 m $\times$ 1.8 m individual farrowing pen, this change in load distribution directly impacts the structural ambient vibration, which can be detected via vibration sensors attached to the surface.

The surface-mounted vibration sensor captures these changes in surface ambient vibration. When the load distribution changes, the modal properties of the structure (e.g., fundamental frequencies, mode shapes, and damping ratio) shift, changing the frequency response of the ambient vibration. In addition, when excitation (e.g., a piglet running) is applied as dynamic point load, it induces the surface to deform and un-deform, which generates predominantly Rayleigh-Lamb waves [89]. Piglet nursing and piglet play induce waves of this type. These waves propagate through the pen structure and can be captured by the vibration sensor as impulsive signal segments.

The feature analysis we perform on each vibration signal to track various animal activities is carefully designed to reflect our physical knowledge of the resulting structural responses. For example, we use the frequency characteristics of the load distribution change for sow lying detection,

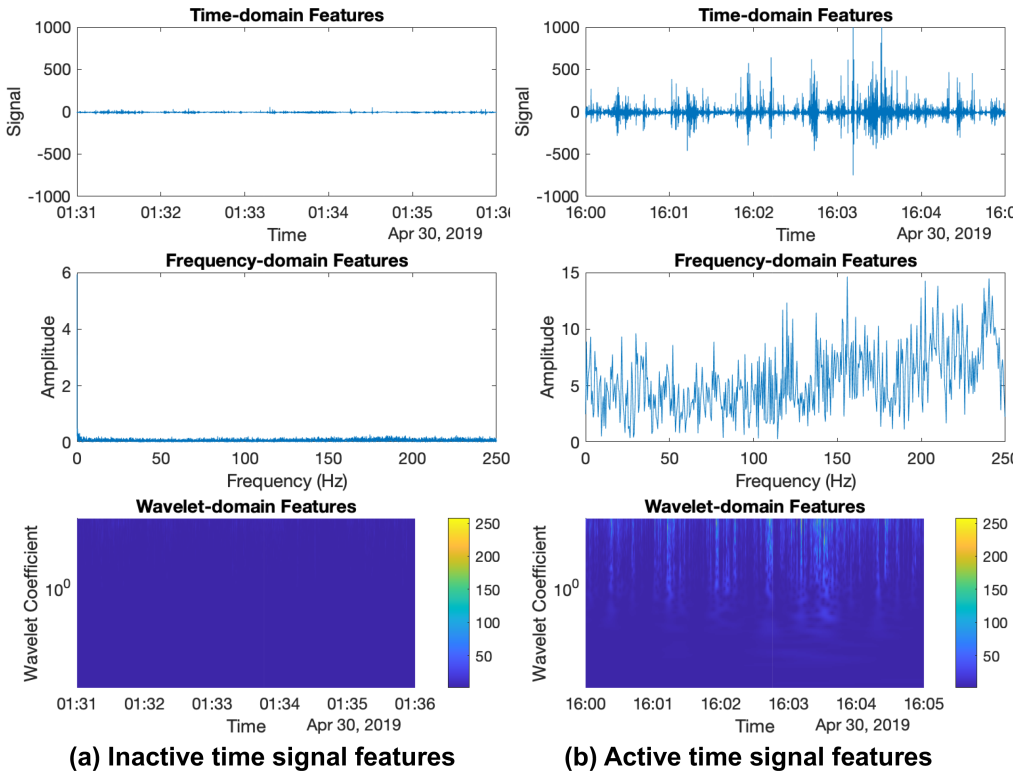

Fig. 5. Representative vibration features from (1) time-domain, (2) frequency-domain, (3) wavelet-domain, extracted from active and inactive times during a day.

while our knowledge of impulsive signal propagation enables the detection of piglet nursing. Both of these help us track piglet growth, characterized by impulsive activities from increasingly heavy piglets.

We use the techniques below to extract **general features** from our vibration data, visualized in Figure 5:

- **Time-domain signal features**: Here, we look at the maximum, minimum, mean, and variance of signal segments, which typically contain information about the intensity of the animals' movements. Since the sow is much heavier than the piglets in the farrowing pen, she induces stronger vibration signals than the piglets. These features allow activity separation between the sow and the piglets. In addition, the signal energy allows us to detect the strength of the motion. For example, the comparatively smaller motion of typical nursing activity induces vibrations with lower energy, while active piglets (i.e., more than five piglets running around) induce higher energy signals.
- **Frequency-domain signal features**: For this analysis, we extract the maximum, minimum, mean, and variance of the Fourier Transform of each signal segment. These features provide valuable information about the types of force that the sow or piglets exert against the floor. For example, the sow's standing posture results in vibration data with a higher, wider frequency band because the vibration starts at the points where the sow's hooves meet the ground. In contrast, the signals from the lying posture have a narrower frequency band and lower frequency because they result from a load more uniformly distributed across the

sow's body. These signals are concentrated at about 25 Hz, which may be the fundamental frequency of the structure.

- **Wavelet-domain signal features**: Here, we calculate the maximum, minimum, mean, and variance wavelet coefficients of each signal segment. The wavelet coefficients are defined as the signal magnitudes after the wavelet transforms, which represent the vibration characteristics in both time- and frequency-domain. Therefore, wavelet coefficients capture the relationship between time- and frequency-domain information, allowing us to relate the activity intensity and type through time-frequency dependency.

4.2 Monitoring Piglet Behavior Patterns with Structural Vibration

The vibration response of the structure to piglet movement can be demonstrated when monitoring daily and weekly periods of the preweaning cycle. Specifically, monitoring the energy of the vibration signal over weeks allows for the tracking of piglet growth, discussed in Section 4.2.1. In Section 4.2.2, we show that more detailed characterization using time, frequency, and wavelet-domain features can be used to monitor patterns in daily piglet behaviors.

4.2.1 Long-term Weight Monitoring. Long-term weight monitoring over the lactation period is essential to increasing the productivity of pig farms [56]. Understanding the weight gain per pen would help the producer estimate the average litter gain continuously over time, indicating piglet and sow health status and farm productivity. In practice, this information will help to evaluate the efficiency of the current farming strategy and lead to higher productivity through follow-up iterations of adjustments.

In this study, we estimate the cumulative weight of the piglets in the same pen (who share the same mother). This provides a reasonable estimation of the productivity of the mother pig, which serves as an important basis for sow phenomics and management. The piglets' weight gains are reflected by their stepping forces on the ground; we can establish long-term weight profiles based on their day-to-day activity intensity patterns. On a daily basis, piglets are active at different times for different activities such as suckling, playing, resting, and so on. The intensity and type of activity vary as their body weight increases and behavior patterns change. However, this growth occurs slowly over time and is hard to see day-to-day.

To capture the long-term weight gain for each pen, signal energy is an effective indicator, because it is the cumulative energy of the floor vibration generated by the pigs, representing the overall activity intensity over time. To quantify the relationship between vibration signals and piglets' weight gain, we conducted a correlation analysis between the signal energy variation and weight increase over the lactation period.

We first calculate the normalized signal energy to accommodate each sensor's differences in signal magnitudes. To normalize the signals, we first subtract the cumulative daily energy by the lowest energy among all days and then divide it by the difference between the highest and lowest energy so the values are between 0 and 1.

With the ground truth for the weight gain of the piglets and the signal energy calculated from the sensors, we then conduct hypothesis testing using t-statistic and set our null and alternative hypothesis as $H_0 : \rho \leqq 0, H_A : \rho > 0$, where ρ is the correlation coefficient. If the correlation coefficient is significantly different from zero (i.e., the null hypothesis is rejected), then we can verify the correlation between signal energy and piglet weight gain.

In light of the observation that signal energy is sensitive to sensor reliability, we use sensor redundancy to cope with unreliable observations. Since each sensor produces a signal energy value and there are five sensors in each pen, we dropped the faulty sensors and took the average of the normalized signal energy for the rest of the sensors. We will discuss the results in Section 6.6.

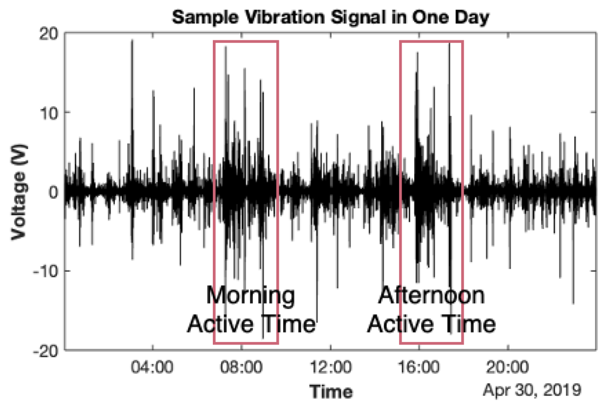

Fig. 6. Sample vibration signal over one day with morning and afternoon active times.

4.2.2 Short-term Active Level Monitoring. Short-term active level monitoring refers to the daily and hourly pattern clustering of the pig's behaviors. It is important to provide timely pig health status and activity patterns to detect abnormal shifts in daily farm operations. For example, suppose the active level during the afternoon feeding session is significantly lower than usual. In that case, the farm staff will need to check on the health status of the pigs or adjust the feeding amount.

To keep track of the active level of the pigs, we utilize the time-, frequency-, and wavelet-domain features extracted in Section 5.1 to discover the patterns and trends in pigs' daily and weekly active levels. We first define different time resolutions to better assess the activity patterns, including: (1) daily (including morning, afternoon, and night), (2) weekly (including different weeks during lactation).

For example, Figure 6 shows the vibration signals from one sensor on a typical day. We observe two typical active periods for the morning and the afternoon, characterized by larger signal amplitudes within a two-hour duration. These two active times correspond to the feeding and farm staff check-in time on the farm.

To visualize the active levels and detect abnormal behaviors, we conduct **principal component analysis (PCA)** to reduce the feature dimensionality. The active times form visually distinguishable clusters after the dimension reduction (discussed in Section 6.6). With these clusters as our reference for healthy piglets, we can detect abnormal behaviors represented by data points that deviate from the cluster centroids. Once we collect enough data points through long-term monitoring, the active period at different times will be more noticeable, and the results will be reliable. We then predict the active level using the **K-nearest neighbors (KNN)** classifier. This is because it captures the gradual change between different active levels by considering the distance between the data samples during classification. With this knowledge, the farm staff can obtain insights into the piglet's daily and weekly patterns, which help them to select good mother pigs to increase productivity and detect anomalies to decrease the lactation mortality rate.

4.3 Monitoring Sow Behavior Patterns with Structural Vibration

The vibration response of the structure to sow movement can be demonstrated when monitoring different periods of the swine farrowing and lactation cycles. In Section 4.3.1, we discuss how analyzing the vibration signal in the days before farrowing can predict the onset of farrowing in advance. In Section 4.3.2, we show how the process of farrowing can be characterized through structural vibration.

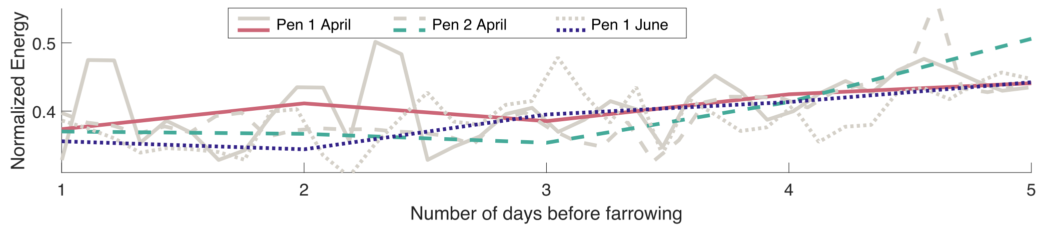

Fig. 7. Daily signal energy increases right before farrowing from three different farrowing cycles in our first deployment location. Behind the daily energy, we show the grayed-out energy for six-hour windows with a sliding window of three hours to show the highly variable nature of the sow activity can obscure the detection of pre-nesting behavior.

4.3.1 Detection of Nesting Behaviors. The farrowing process carries severe risks for the piglets, with an average survival rate in large herds of only 87% [83]. Studies show that monitoring the farrowing process can halve the mortality rate during this time [41]. By detecting a sow's prebirth nesting behaviors through their activity, our vibration sensors can predict farrowing the day before it begins. These nesting behaviors are inherited and universal among the pig and boar family *Suidae* [92]. In the wild, the sow will first isolate herself from the herd and look for a suitable location, then start building a nest 24 hours before birth. The most intensive nest-building activity occurs 12 to 6 hours before farrowing. The primary nest-building activities include digging a shallow hole and then collecting and placing materials such as branches and bushes to keep her piglets warm and sheltered. In the farrowing pen environment commonly used in production farming, the sow does not have the ability to engage fully in these behaviors. Instead, she paws at the floor, changes position frequently, and spends more time standing during this period [92]. Studies had shown that when housed in pens, sows transition from an average of 3 hours a day spent standing in the week before birth to an average of 7 hours a day spent standing in the 24 hours before birth, while the number of standing–lying transitions increases fivefold [64]. We hypothesized that these changes in behavior cause significantly more movement in the farrowing pen and, consequently, more energy in our vibration signal. Figure 7 shows the mean normalized vibration energy across sensors for the five days preceding birth from three farrowing cycles in our first deployment. For each cycle, the daily energy is shown in color. For each of our farrowing cycles, the daily energy is fairly steady until it increases on the final day, which we relate to the pre-nesting behaviors earlier described. Behind the daily energy, we show the grayed-out energy for 6-hour windows with a sliding window of 3 hours. We can see that as the sow's activity is highly variable, even 6-hour windows are too precise to see the overall increase in activity that precedes farrowing clearly. We found a single energy reading for each 24-hour period to be the most useful in predicting farrowing. We normalize this reading by the number of collected samples for that day to control for lost sensor data and add *algorithmic fault tolerance*. We can also use our characterization of sow posture to recognize sow nesting behaviors, which we will demonstrate in the evaluation.

4.3.2 Farrowing Process Characterization. Farrowing process monitoring is critical to ensure the successful farrowing of the sow and the survival of the newborn piglets. Monitoring the farrowing process involves capturing the sow's movement and the time when individual piglets are giving birth. This enables the farm staff to identify issues, including stillbirths, weakness/exhaustion, and long duration between the birth of individual piglets, and then intervene to improve the piglet survival rate. Labor shortages in rural areas have resulted in under-staffed swine production units, thus, having a system to notify workers of which sows to focus their attention will improve farrowing success and more efficiently use limited labor resources.

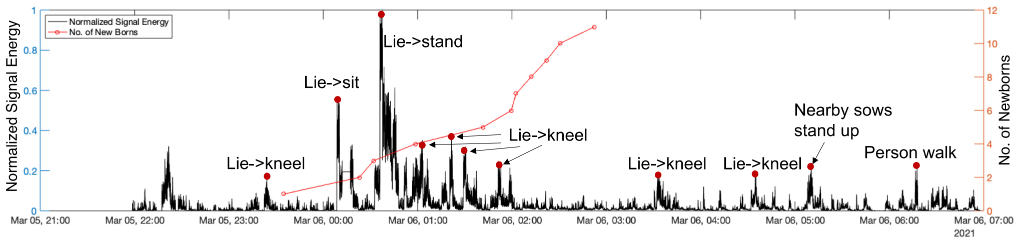

Fig. 8. A representative illustration of the signal energy trend during the farrowing process.

A normal farrowing process takes 2–4 hours to complete neonatal delivery. As the sow approaches the delivery phase, she will become either calmer or more restless as the uterine contractions intensify, depending on the sow's farrowing experience. This can be indicated by the frequency of posture changes. Before the birth of the first piglet, the sow lies down on one side and has intermittent abdominal muscle straining, usually accompanied by shivering (when the sow draws her upper hind leg upwards). After the first born, the straining usually becomes milder gradually and only intensifies just before a piglet expulsion. During a typical farrowing process, the sow gives birth to an average of 10 piglets at an interval of 10–20 minutes, with a resting period after the first 2–4 piglets.

We observe the farrowing process from the structural vibration signals to understand the stages of farrowing with the change of sow postures. Figure 8 shows the changing signal energy during the process of farrowing from a sow. From this process, we observe that the sow appears to be calm before the farrowing with only slight adjustments of postures within an hour. As the farrowing process starts, the sow stays calm for around 30 minutes and then starts changing postures frequently for 10 minutes before the birth of the second piglet. Between the second and the sixth births, the sow appears to be restless and frequently changes from lying to kneeling, even standing for 10 minutes. The last six piglets are delivered in a row at less than 10-minute intervals. During that time, the sow remains motionless on the floor. The complete farrowing process lasts 3.5 hours from March 5th 23:25 to March 6th 02:52. The sow resumes the regular kneeling and lying activity 30 minutes after the farrowing.

4.3.3 Sow Sickness Characterization. Sow sickness during farrowing can significantly increase the piglet mortality rate during the lactation period. Such diseases include **mastitis, metritis, agalactia (MMA)**, gastric ulceration, and so on [7, 33]. These diseases result in reduced milk production, loss/deprivation of appetite, fever for the sow, vomiting, and a high risk of death for the piglets. Detecting sickness through abnormally low signal energy can provide timely treatments to the pigs.

To understand how sickness is reflected through the structural vibration signals, we look into an example from our deployment when the sow had mastitis, which caused sickness (enteritis) in the piglets. As shown in Figure 9, the beginning of the sickness is characterized by a slight drop in cumulative signal energy per day. Typically, the energy in the signal keeps increasing as the piglets gain more weight over time. Thus, the drop in signal energy over several consecutive days clearly indicates abnormal behaviors. On the 4th day of decreasing energy, the sickness was observed by staff as the piglets started vomiting and became inactive. Treatment was provided to both the sow and the piglets on the following days to relieve the symptoms. The signal energy reaches the minimum on January 30th, and the active level in the pen starts to resume in the following week. On February 2nd, the veterinarian checked that the piglets recovered from the disease, and the signal energy soon increased in the following days.

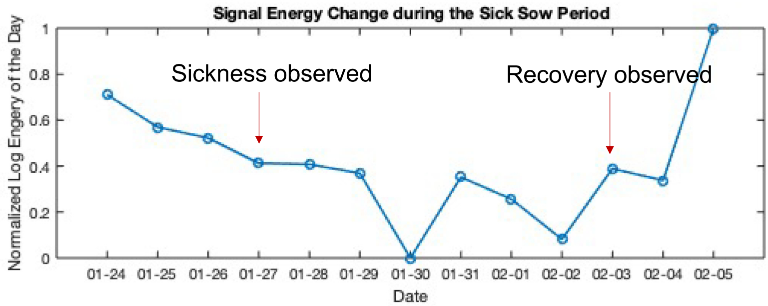

Fig. 9. A representative illustration of the signal energy dropping during the sickness period.

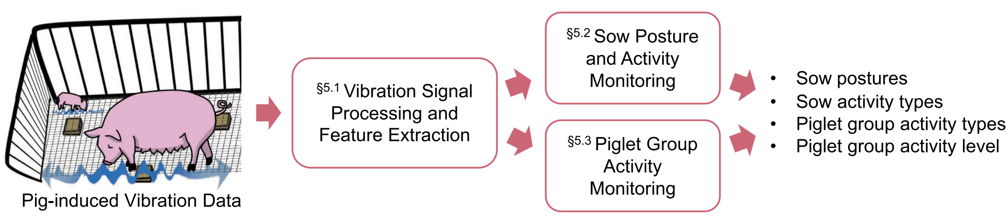

Fig. 10. A system diagram for sow and piglet activity recognition through structural vibrations induced by their daily behaviors.

5 SWINE ACTIVITY RECOGNITION

In this section, we recognize critical swine activities to understand their daily behaviors in the farrowing pens, as described in Figure 10. To achieve these, we first pre-process the vibration signals and extract features that contain physical characteristics of the swine activities (Section 5.1). Then, we use supervised learning to recognize the activities of the sow and the piglets. These activities include (1) posture changes, ingestion, and excretion of the sow (Section 5.2) and (2) nursing and activity level of the piglets (Section 5.3).

5.1 Vibration Signal Processing and Feature Extraction

To extract swine activity information from the vibration signals, we (1) pre-process the signals to remove the noises and then (2) extract features that can reflect the general characteristics of different activities. As discussed in Section 4, the insights behind these features are interpreted based on their physical meanings.

5.1.1 Signal Processing for Swine Activity Recognition. Structural vibration signals induced by the sow and/or the piglets are pre-processed to remove environmental and sensory noise. First, a low pass filter of 250 Hz is applied to remove high-frequency noises caused by the electrical components and sensors. The 250 Hz cap was chosen based on prior knowledge about the range of effective signals induced by activities. This operation also reduces the amount of data to be dealt with, which reduces the computational time by half for later analysis. Then, an adaptive Wiener filter is applied to remove the white noise in the signal, which allows activities that result in lower amplitude signals, such as piglet nursing, to be observed in the ground vibrations.

After noise filtering, the structural vibration signals are then processed in 5-second sliding windows for feature extraction (see Figure 11). The length of the sliding window was chosen based on the tradeoff between accurate prediction and the duration of a single event. A longer window

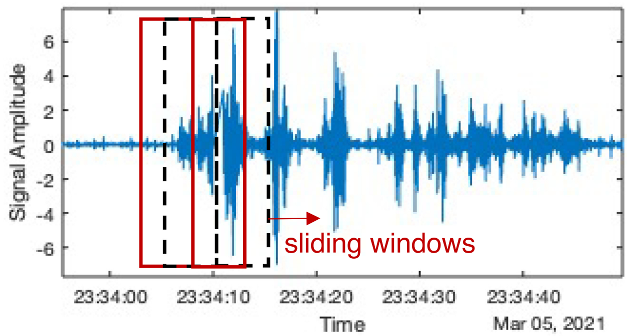

Fig. 11. A representative sample of pre-processed ground vibration signals with sliding windows.

typically provides more accurate prediction, because it allows more of the signal to be seen so it is more robust to abrupt noises. However, the sow may change postures during that long window, leading to low time resolution in segmenting different activity types. In our study, the length of 5 seconds was chosen because we observed that the minimum duration of the sow keeping the same posture is typically 5 seconds (which is typically sitting, because it is a transition posture between kneeling and standing). The same sliding window length is chosen to predict piglet group activities based on the same consideration. These sliding windows have a 50% overlap in time, which captures the temporal dependency between two adjacent windows.

5.1.2 General and Task-specific Feature Extraction for Swine Activity Recognition. Vibration signal features that represent their motions are extracted to recognize the posture and feeding activities of the sow and piglets over time. These features are divided into two main categories: **(1) general features** and **(2) task-specific features**, as summarized in Figure 12. The general features enable a more efficient machine learning framework when different types of activities happen simultaneously. Extracting general features also enables system flexibility to adapt to new activities that need attention on the farm. Task-specific features provide accuracy improvement on top of the general features to precisely recognize individual activities and improve sample efficiency for these tasks.

To enable both the **generalizability** and **precision** in feature extraction, we first extract a set of general features to cover the breadth of our monitoring tasks and then select or add task-specific features to capture the signal characteristics that are unique to a certain activity type. For example, in piglet nursing detection, we first pre-train the model using general features to determine the most important features among all; then, we characterize the nursing activity and extract nursing-related features such as the mean absolute amplitude of the signal; finally, we combine these features for real training and testing.

- **General features:** The general features include the mean, variance, maximum, and minimum values of signal magnitudes in the time-, frequency-, and time-frequency- domains (as discussed in Section 4.1), which are found to be effective in classifying different types of activities in prior works [12, 68, 70]. Since they contain information about the activity type and intensity, these features are generally applicable for recognizing different activities of the sow and piglets and are reusable for new types of activities. As a result, extracting these features significantly reduces the computation time, because they are shared among different recognition tasks.
- **Task-specific features:** The task-specific features are customized features for specific activity recognition tasks to improve the model performance. For example, the sow ingestion

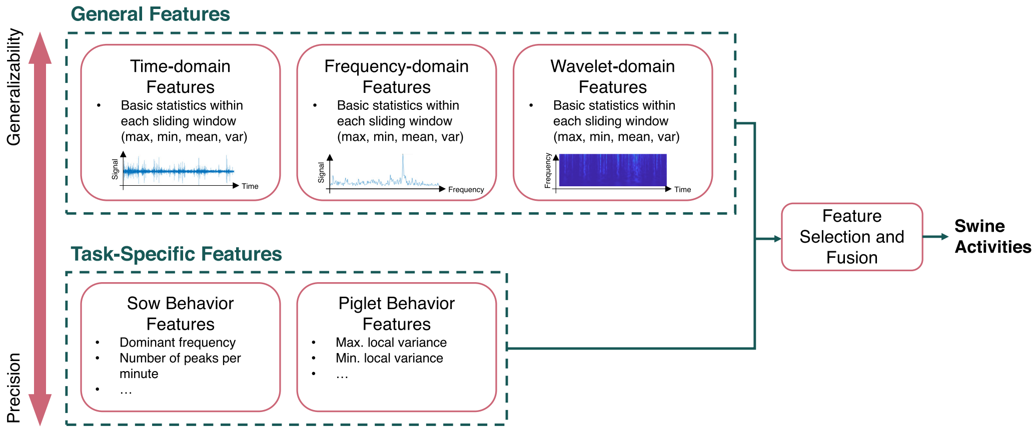

Fig. 12. Fusion of general features and task-specific features for swine activity recognition. The general features enable generalizability of various tasks, and the task-specific features enhance the accuracy of each individual task.

behavior is predicted through the interaction between the sow and the feeding tray and water nozzles, so analyzing signal amplitude distributions within a specific frequency band corresponds to that interaction (e.g., 20–30 Hz) and produces high accuracy in predictions. These features contain physical and behavioral domain knowledge, which serves as an effective complement to the general features.

With both general and task-specific features, we can relate the structural vibration with the physical characteristics of the growing piglets by comparing them with the ground truth, which further enables the prediction and interpretation of vibration-based swine activity recognition.

Features extracted from the signals are then compressed through **principal component analysis (PCA)** to reduce the sampling sparsity in the feature space. With PCA, the distribution of samples is visualized, and the basis vectors are examined to assess the importance of the features and the separability of different postures/activities. A preliminary test shows that the first 10 components cover 98% of variance in a sample day of vibration data.

5.1.3 Interpretable Statistical Modeling and Prediction of Pig Activities. To predict and recognize various pig activities, we choose the tree-based machine learning models (i.e., the random forest and gradient-boosted tree) because of their high learning capacity and low cost in the data processing facility. In addition, recent advancements in machine learning suggest that tree-based classifiers have superior performance in optimizing the tradeoff between model interpretability and capacity in high-stakes applications, such as human/animal healthcare and financial investments.

The random forest and gradient boosting tree classifiers are both ensemble learning methods that classify pig activities by leveraging a multitude of decision trees to learn the complex data patterns in the vibration signals. By combining multiple decision trees, the model mitigates the over-fitting problem in individual decision trees while enhancing the model capacity through the cumulative power of multiple trees. The main difference between these two models is how the decision trees are created and aggregated: While the random forest builds each tree independently, gradient boosting builds each tree to correct the error from the previous one.

Both tree-based models are highly interpretable such that the feature importance is obtained based on the nodes' impurity and probability in decision trees. Therefore, the farm owners and animal researchers can understand how the decision is made by visualizing the weight of each individual feature.

Moreover, these tree-based models produce similar accuracy as the state-of-the-art deep learning techniques during our evaluation. Our results show that our model matches or slightly outperforms the **convolutional neural networks (CNN)** by 4% in accuracy. The details will be discussed in Section 6.

5.2 Sow Posture and Activity Monitoring

Sow posture and activity monitoring provide important information about her health status and her capability to take care of the newborns [53, 61, 87]. Typical daily activities of the sow include posture changes, ingestion, and excretion. In this section, we detect these activities and make predictions for their current activity status by learning the representative features for each activity from the vibration signals.

5.2.1 Sow Posture Monitoring and Posture Change Detection. In this section, we monitor the sow's posture and detect the transitions between postures. Monitoring the sow's posture is an important indicator of her health status and comfort level. For example, standing is an indication of heat stress. Monitoring the duration of standing allows the farm to ensure the room temperature is suitable. In addition, up and down movement duration indicates the risk of piglet crushing [53, 61, 87]. A sudden move downwards from standing to lying may crush the piglets underneath, leading to an increased mortality rate. Prior to giving birth, frequent postural changes are also an indication of the onset of labor and/or dystocia, signaling a critical need for human assistance with piglet delivery.

The postures of the sow are divided into three categories: standing, sitting/kneeling, and lying (see Figure 13). The transitional posture change is categorized into up and down motions. When the sow moves from lying to sitting/kneeling or from sitting/kneeling to standing, the motion is considered as "up." When the sow moves from standing to sitting/kneeling or from sitting/kneeling to lying, the motion is considered "down." Since the up and down motion depends on the posture before and after, we first classify the postures within each sliding window. We then use the predicted posture to determine if there is an up or down motion between the adjacent windows.

Sow Posture Classification. To predict the current posture of the sow, we apply a gradient-boosted tree classifier with the general features extracted in Section 5.1.2. The gradient-boosted tree was chosen because it enables non-linear fitting by adding a large number of weak learners and handles missing data automatically due to short-duration hardware disconnections. The main intuition behind the model is as follows: Different postures induce different impulses in the frequency domain so they can be distinguished through the frequency-domain features. When the sow is in a standing posture, she induces higher frequency vibrations; when she is in the sitting/kneeling posture, signals with lower frequency than standing postures are induced; when the sow is lying, the dominant frequency accumulates around the natural frequency range of the structure.

While the vibrations induced by the sow dominate the overall signal, piglets may experience bursts of activity that induce significant impulsive excitation concurrent with sow behaviors. Signal windows containing these piglet movements appear similar to the standing sow, resulting in errors in predictions. In addition, there are environmental disturbances on the farm, such as a person walking, water discharging, or intense activities from the nearby pen, which also leads to misclassifications in sow posture predictions. To correct the predictions from these windows, the predicted results are then smoothed through a moving majority vote algorithm over every five windows. This approach will be discussed and evaluated in Section 6.4.1.

Sow Up and Down Motion Detection. Detecting up and down motion means capturing the sow's transitions between standing, sitting/kneeling, and lying, which are short-duration events

Fig. 13. Representative images of different sow postures observed during the deployment.

that induce significant vibrations. To detect up and down motion in the vibration signals, we designed a peak-picking algorithm over the moving energy of signals, because the sow's change of postures typically induces significant impulses to the ground. If an energy peak is detected within two consecutive windows with different postures, then an "up" or "down" label is assigned to the 5-second period centered around the energy peak. However, this energy change may also result from other activities, such as sudden excitement from the piglets and environmental disturbances. To verify and classify up and down motion after the detection, we leverage the predictions in the static postures to infer the time of motion and type of motion, because the up and down motion can only occur between two different postures. For example, if two consecutive windows are predicted as standing and lying, then a "down" motion is very likely to occur in between.

5.2.2 Sow Ingestion and Excretion Detection. In this section, we monitor the sow's ingestion and excretion activities to assess her digestive status. Sow ingestion and excretion detection is key to understanding sow health. The frequency and duration of ingestion events, as well as the frequency of excretion events, are critical indicators of digestive health, where common ailments include ulcers and constipation. Early warning signs for these two problems would facilitate early treatment and rapid recovery. In addition, ingestion patterns can predict other common health problems, as intake is reduced when an animal has a fever. A common disease is **mastitis, metritis, and agalactia (MMA)**, leading to a high incidence of lactation mortality in piglets [85]. Finally, excretion patterns dramatically increase in preparation for farrowing and are an important behavior signaling the onset of parturition.

Sow Ingestion Detection. Sow ingestion activity includes eating and drinking (see Figure 14). They are detected mainly through task-specific features based on the vibration characteristics of the feeding trays (for eating) and the water nozzles (for drinking) because of the unique physical interactions between the sow and the feeding components. The feeding tray and the water nozzle have different materials and shapes and therefore induce vibrations in different patterns from the floor. Feeding trays are connected to the pen through two metal bars. When the sow is eating, the metal bar knocks the pen through irregular impulses, which generate high-frequency vibration signals. In contrast, the water pipe for the drinkers attaches to the pen tightly, which generates regular and low-frequency impulses.

While sow ingestion activities induce unique patterns in ground vibrations, one significant challenge is the unbalanced sample between ingesting and not ingesting, which introduces biases toward the majority class and fails to detect ingestion events. To overcome this challenge, we assign higher weights to the loss function for the ingestion class. The weight value depends on the proportion of the number of samples in these two classes. Finally, sow ingestion activity is detected through a random forest classifier. The parameters of the classifier were chosen heuristically during preliminary testing with three days of data.

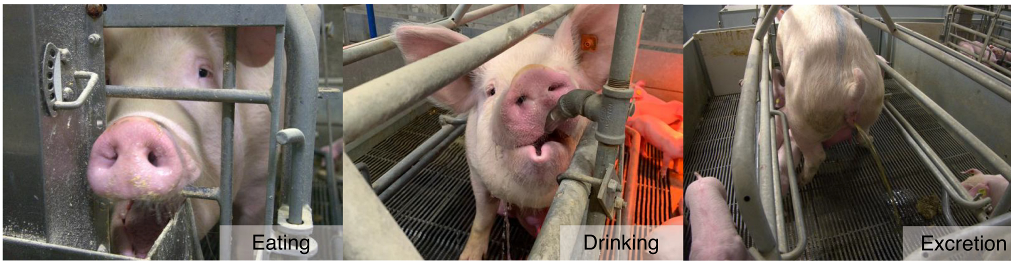

Fig. 14. Representative images of sow ingestion and excretion: (1) eating from a feeding tray, (2) drinking through a water nozzle, (3) excretion.

Sow Excretion Detection. Sow excretion activity includes urinating and defecating (see Figure 14). While these two activities are essential indicators of the sow's digestive health, they are challenging to detect, because the vibrations induced from liquid and solid dropping on the floor are significantly smaller than the sow's motion. To overcome this drawback, we utilize the insights that (1) the sow typically excretes when she is standing, and (2) the sensor that is closer to the back of the sow is more sensitive to excretion.

Therefore, we detect the sow excretion activity based on the posture predictions and then learn general and task-specific features from the vibrations captured by the two sensors at the back, because the sow is typically constrained to face forward. The task-specific features include the amplitudes in high-frequency ranges (i.e., more than 100 Hz) and the proportion of high-frequency to lower-frequency (i.e., less than 30 Hz) amplitudes. The excretion detection algorithm is activated when the sow posture is predicted as standing. Then, we apply the random forest classifier to detect urinating and defecating activities using the two sensors at the back. The urinating activity is characterized by a short duration of signals with random and similar maximum amplitudes (i.e., like white noises but with much higher amplitudes). The defecating activity is characterized by a series of irregular impulses on the floor.

Similar to the sow ingestion activities, the sample number of the excretion activities is significantly unbalanced compared to the overall standing time. Therefore, we apply a weighted loss function during prediction.

5.3 Piglet Group Activity Monitoring

Characterizing piglet group activity is critical for monitoring piglets' health and understanding their development stages. This is because the activity of normal piglets shows periodic patterns in response to variations in light, temperature, and feeding routines. A sudden change in activity pattern will indicate an acute change in health status. If a group of piglets is not hitting the target activity level, then that is an indication that the producer should be alerted to watch this particular litter. For example, if piglets are not nursing often enough or long enough while sleeping longer than usual, then they may be at risk for illness or starvation. However, if the piglets are nursing well, then their sow displays good maternal behaviors and may be a good candidate to breed additional litters. To this end, we chose three critical piglet activities to characterize: nursing, sleeping, and being active.

5.3.1 Group Activity Characterization. Piglet group activity characterization refers to the cumulative numbers of piglets engaged in different activities, such as nursing, sleeping, and so on. The piglets in each pen are regarded as a single group. The number of piglets engaged in each activity defines the intensity of that activity. There are two main challenges in characterizing the

Fig. 15. Typical piglet activities: (1) nursing, (2) sleeping near the sow, and (3) being active and walking/running around.

piglet group activity. The first challenge is that it is hard to accurately count the number of piglets engaged in different activities due to the small size of the piglets and the reliance on a top-down camera. Newborn piglets are too small to distinguish when they are crowded together, and often one piglet is hidden behind another in the frame or behind part of the sow. Piglets frequently fall asleep while still suckling, and it can be hard to tell if they are sleeping or nursing. Nursing frequency and duration after labeling with our study were found to be within the expected ranges [2, 43]. The second challenge is that it is more demanding to predict piglet group activity than to detect a specific sow activity because it involves more piglets and activities, which often overlap within a group. To address these challenges, *PigSense* divides the piglet group activities into three types: nursing, sleeping, and being active. Each activity type is then characterized separately, which allows us to use targeted task-specific features based on physical and behavioral domain knowledge to more precisely characterize each activity. It also allows us to handle cases of overlapping activities, as the activities are characterized in parallel.

Defining Group Activity Types and Levels. Piglet activities can be divided into nursing, sleeping, and being active. Nursing is a complex, multi-phase process defined by four stages: initiation, pre-let down, let down, and post-let down, which represent approaching the udder, stimulating the udder, receiving the milk, and post-milk suckling. When labeling our data, it is difficult to distinguish the final three stages by sight. Prior approaches to this issue when monitoring piglets opted to disregard the individual phases, instead tracking each overall suckling period [84, 88]. Therefore, for individual piglets, we define nursing as suckling at the udder. Sleeping represents any activity during which a piglet stays quiet and still. Being active refers to other activities except nursing and sleeping, such as wandering, running, playing, and so on. Figure 15 shows these three typical activities of piglets.

Each group activity is divided into different intensity levels based on the distribution of the number of piglets engaged in this activity. The exact division ranges are shown in histograms in Figure 16. For nursing, if there are 0 to 4 piglets nursing, then it is defined as light nursing level; if there are 5 to 9 piglets nursing, then it is defined as medium nursing level; if there are 10+ piglets nursing, then it is defined as high nursing level. This corresponds with the definition given by Thomsson et al. and used in our previous work, which defines "nursing/suckling" as any time when at least five piglets are suckling [10, 84]. By this definition, "medium" or "high" nursing would both be considered nursing, while "light" nursing would not be considered a nursing event. Sleeping intensity levels include light (0 to 2 piglets) and high (2+ piglets). The intensity levels of "active" include light (0–2 piglets), medium (3–6 piglets), and high (7+ piglets). Classifying the piglet group activities into different intensity levels has two advantages: (1) Minor artificial counting errors have a negligible effect when focusing on levels instead of the particular number of piglets engaged in

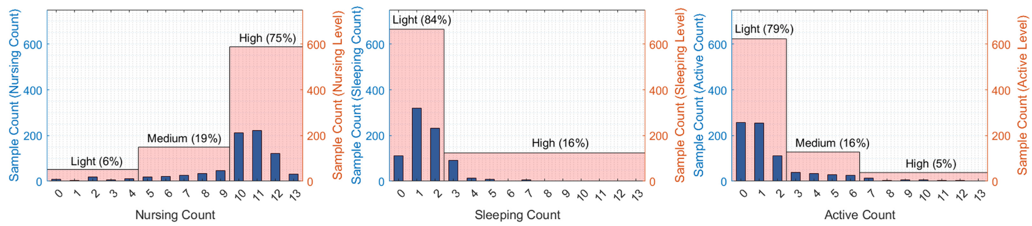

Fig. 16. The distribution of the number of piglets engaged in three activities: (1) nursing, (2) sleeping, and (3) being active and division ranges of each group activity level. For example, for nursing, if there are 0 to 4 piglets nursing, then it is defined as light nursing level; if there are 5 to 9 piglets nursing, then it is defined as medium nursing level, and so on.

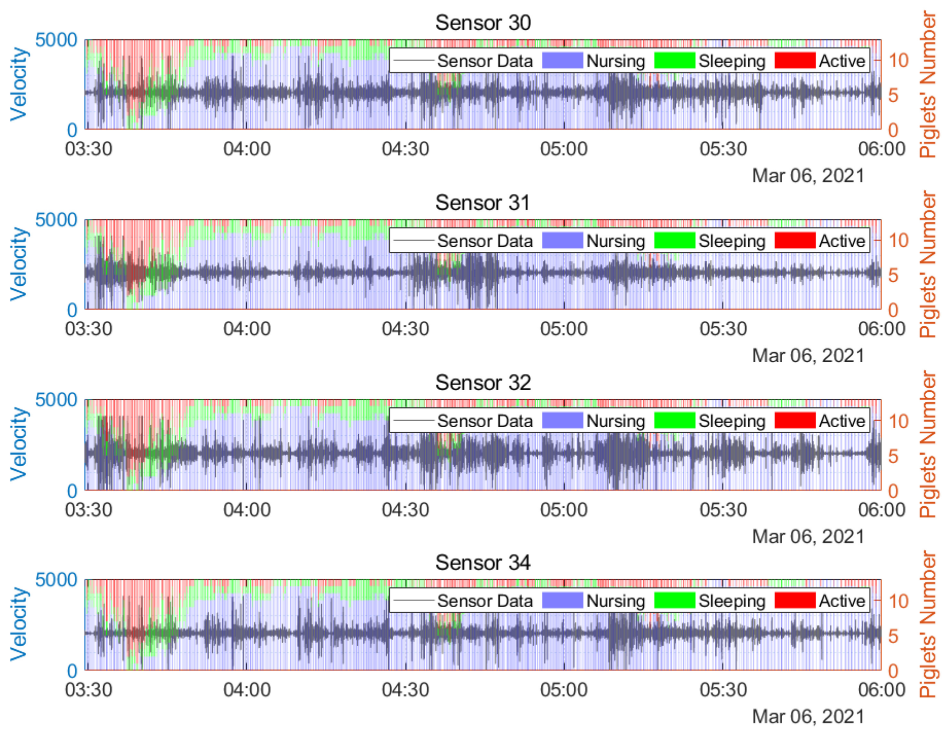

Fig. 17. Group activity overview. The figure gives an overview of piglet group activity composition in the first two-and-a-half hours after sow farrowing. Four subplots show four different sensors in a pen. In each subplot, the black line indicates the sensor's vibration data, which is different from other subplots, since the sensors' locations are different. The colored stack bars represent the number of piglets engaged in a specific activity.

an activity. (2) The resulting description of the piglet group activity is more intuitive. For example, the group activity at 4:30 am can be easily depicted with a set of activity levels: high nursing level, light sleeping level, and light active level.

Figure 17 presents an overview of the piglet group activity in the first two-and-a-half hours after sow farrowing. The black line in each subplot represents the vibration data (velocity) of different sensors, whose layouts can be seen in Figure 21, pen 3. The colored bars indicate the number of piglets engaged in three activities. The figure shows that nursing and being active have obvious

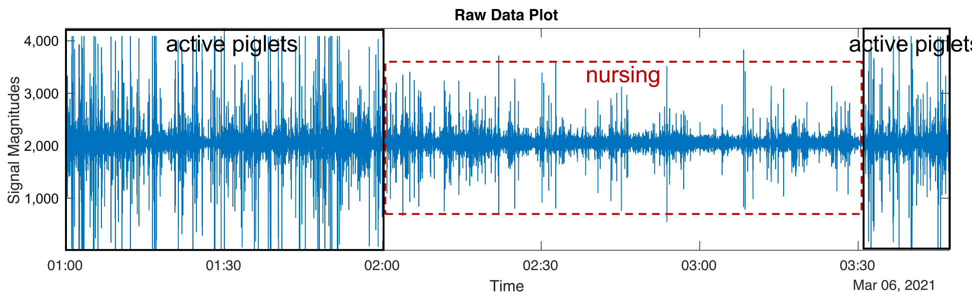

Fig. 18. This representative plot shows that nursing behavior creates a lower amplitude irregular pattern in the vibration signal when compared to active piglets.

periodic patterns, which align with our expectations. The piglet group tends to be very active every 40 to 60 minutes. The number of piglets engaged in nursing tends to be small when the number of piglets involved in being active is large. The highest amplitude vibration data corresponds to the case where more piglets are engaged in being active. The vibration data varies between subplots, as sensors in different locations are sensitive to different activities. For example, Sensor 32, in the center of the pen, shows higher responsiveness to nursing activity.

Classifying Group Activity Levels. *PigSense* builds an activity-level classification model for each piglet group activity. We start by extracting the time-domain and frequency-domain signal features mentioned in Section 5.1.2. Due to the complexity of classifying overlapping activities with multiple piglets, we add various task-specific features to our general features to improve the model performance and then heuristically select features for each activity based on a small test set. Our task-specific features are informed by behavioral knowledge such as the location or timing of specific piglet activities and physical knowledge about the expected wave propagation through the structure caused by various activities. We discuss this domain knowledge and how it informed task-specific features for each classifier in the following sections.

Nursing: Based on our observations, nursing piglets move their heads back and forth in a fast regular motion as they stimulate the sow's udder. This suckling motion of several piglets causes dynamic excitation of the structure, which is captured most clearly by the vibration sensor in the center of the pen, which is underneath the sow's udder. Figure 18 shows a representative sample of vibration data from the sensor in the center of the pen. We can see that the superposition of multiple nursing piglets results in an irregular pattern with lower signal amplitudes, as observed by the sensor. In addition, based on our preliminary observations of the data, the number of peaks tends to decrease as the number of nursing piglets increases. Therefore, we expect that our frequency-domain signal features from the central sensor will effectively capture the changes in frequency caused by the overlapping suckling motion of several piglets. The corresponding frequency and prominence of peaks in the time domain are also extracted as additional features to help quantify the phenomenon.

Sleeping: Unlike the other categories, sleeping tends to be characterized by a lack of other activities, as it does not create excitation of the structure. As with nursing, piglets tend to fall asleep near the sow, so we expect the sensor in the center of the pen to be the most useful. Our challenge here is detecting the stillness of piglets without relying on a quiet environment, as the structure is also affected by sow activity and ambient noise. As piglet activities happen faster than sow activities, we leverage hyper-local time domain features to detect small piglet movements (or lack thereof) within the larger signal segments. Our 5-second signal segment is divided into 1-second frames with a step size of 0.002 second. The variances of each frame are calculated, and

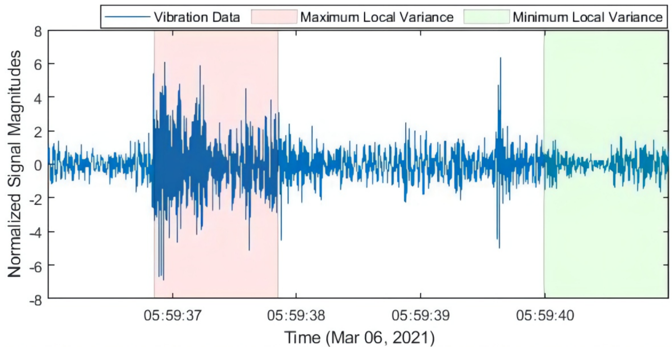

Fig. 19. Local variance features. The figure shows the local variance features in the time domain. Variances of the most unstable parts and the most stable parts are extracted in this case. The blue curve indicates a sensor's vibration data for five seconds. The red-filled area is the most unstable one second, from which period the maximum local variance is extracted. The green-filled area is the most stable one second, from which period the minimum local variance is extracted.

the maximum and minimum variances are used as features, reflecting the amount of local change in the most unstable and most stable parts of the signal segment. Figure 19 shows the local variance features in a single time-domain signal segment. The blue line shows the vibration data, the red-filled area is the most unstable 1-second section with the highest variance, and the green-filled area is the most stable with the lowest variance.

Active: The "active" category includes the widest variety of impulsive motion in the largest possible area, as piglets may walk, run, or play anywhere in a pen, in contrast to nursing and sleeping, which tends to happen near the sow. This piglet motion induces the pen surface to deform and un-deform, which generates predominantly Rayleigh-Lamb waves [89]. These waves propagate through the pen structure and can be captured by the vibration sensors as impulsive signal segments with a wide frequency spread. Therefore, we expect our signal to affect multiple frequency bands and to vary based on the type, intensity, and location of the active movements. To address this, the skewness and kurtosis of the Fourier Transform are extracted to characterize the shape of the signal segment curve in the frequency domain. Skewness can measure how skewed a curve is, and kurtosis is used to measure the relative peakedness of the curve. We also add the variance-based local features discussed in the sleeping category to detect small piglet movements. Short-duration piglet activities such as jumping might be submerged, because the general time-domain features are calculated among the whole signal segments. The local variances are designed to address this problem (Figure 19).

When characterizing piglet group activities, *PigSense* faces the challenge of selecting features sensitive to different group activity levels while also being insensitive to irrelevant activities such as the motion of the sow. Using all possible features would lead to overfitting irrelevant activities in or near the pen. Therefore, after we have added our task-specific features to the general feature set, critical features are heuristically chosen from the initial features. Here, we use the random forest algorithm, which can be applied to rank the importance of variables in a classification problem and speed up our feature selection. Although the feature selection method is outcome-oriented, and essential features are chosen based on their classification performance on the test set, the results match our observations and expectations well.

For classifying piglet group nursing and sleeping levels, only basic statistics of frequency bands and local variance are included as essential features. Other features, such as energy features, other time domain features, as well as time-frequency domain features, are excluded. This is because piglet nursing and sleeping tend to induce more special and regular structural vibrations, which can be reflected in some elementary statistics of frequency bands. Importing local variance features is to eliminate interference from active piglets, since these features are designed to catch momentary piglet movements, such as jumping or turning over.

For classifying the “active” category, more essential features are selected except basic statistics of frequency bands and local variance, including skewness, kurtosis, and the frequency corresponding to the maximum of frequency bands as well as energy features in the time domain. Other time-domain and time-frequency domain features are removed. Local variance features are selected, since they can reflect the intensity of temporary piglet movements. Energy features in the time domain are chosen to measure the intensity of general movements and get rid of the interference of sow’s movements. Particular structural vibration patterns of different “active” levels can be indicated by keeping basic statistics of frequency bands. As a supplement, skewness, kurtosis, and the frequency corresponding to the maximum of frequency bands are also incorporated as essential features for distinguishing frequency bands’ shapes. Because, according to our observations, the shapes of frequency bands tend to be different among different “active” categories, even if they lie in a similar range. More detailed feature selection results will be discussed in Section 6.5.

Before evaluation, all vibration data is normalized to zero mean and one standard deviation to boost the convergence speed of model training. The random forest algorithm is deployed again to classify the final group activity levels, because it does not require data to conform to certain assumptions and is suitable for solving high-dimensional input problems. However, for each group activity, the number of samples in different classes varies significantly (Figure 16), which can cause poor performance in minority classes. Therefore, samples with imbalanced labels are repeated randomly in the training set before being fed into the group activity classification model.

6 EVALUATION

We evaluate our system through long-term deployments in pig farms in Thailand and the United States. In this section, we first introduce the detailed deployment setup in these two sites and present the overall results for sow and piglet activity recognition (Sections 6.1 and 6.2). Then, we discuss the iterative design process of the hardware and the lessons learned over the course of this two-year field deployment experience (Section 6.3). Finally, we conduct a detailed analysis of the results for sow and piglet activity recognition (Sections 6.4 and 6.5).

6.1 Field Deployment Setups

In this section, we provide an overview of our deployment in two pig farms: (1) a commercial farm in Thailand and (2) a research farm in the USA. We deployed our system in these two farms over the course of a year and evaluated *PigSense* in various tasks introduced in Section 5.

6.1.1 Real-world Evaluation at an Operating Pig Farm in Thailand. We deployed *PigSense* for three months at a commercial farm in Lopburi, Thailand, from April 2nd–June 9th, 2019. As the animals used in the study were not used solely in this collaboration and were not supported by our funding, our institutions’ IACUCs determined that a protocol review was not needed for this study. We did not interact with or change the animal environment in any meaningful way, but simply monitored them from afar while the farm continued normal operations.

We installed the sensors in three farrowing pens designed for a single sow and her piglets. A farrowing pen is shown in Figure 20(b). Each pen has 10 sensors installed on the underside of the floor of the pen, 2 each in 5 different locations, as shown in Figure 20(c). In this deployment, we use two configurations for the placement of the geophone sensors as part of our iterative design process described in Section 6.3. First, we glued the sensor directly to the farrowing pen, connecting it

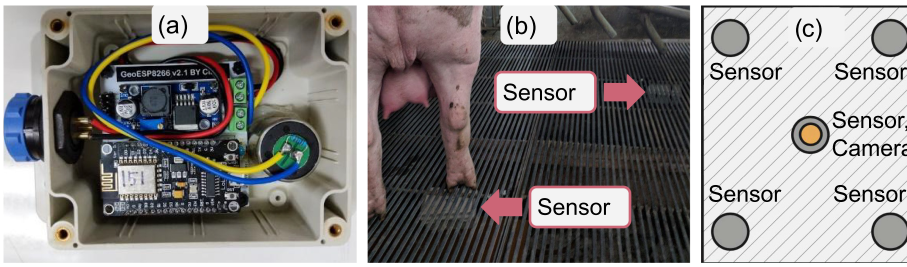

Fig. 20. Our experimental setup at our first deployment in Thailand: (a) Our waterproof sensor box, with a sensor inside and a waterproof connector for power. (b) Our sensor was installed on the underside of a farrowing pen. (c) A diagram of the location of our sensors and ground truth camera in a farrowing pen.

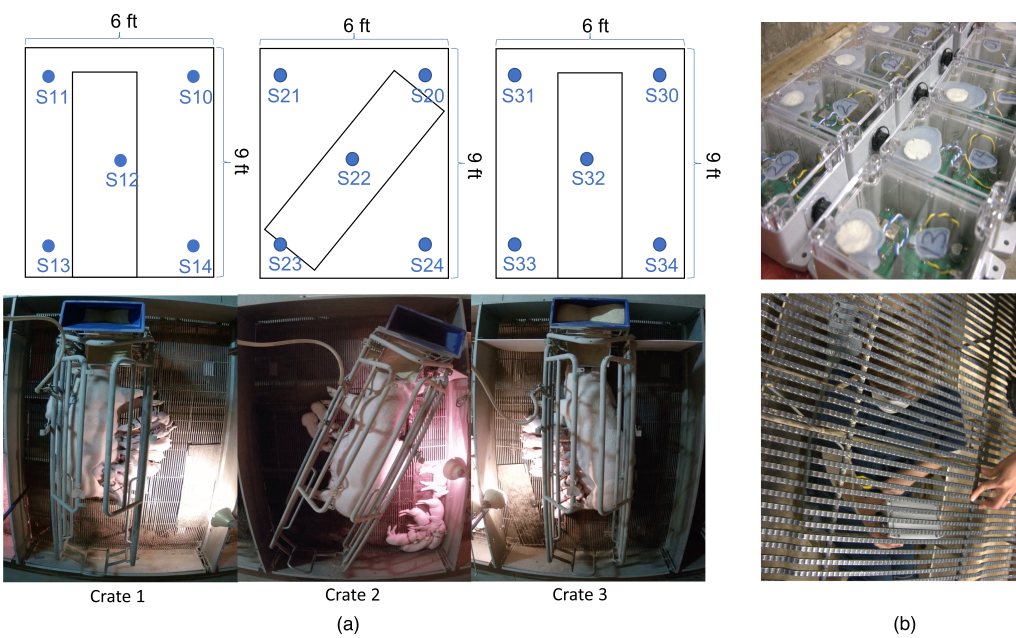

Fig. 21. Our experimental setup at our second deployment in the United States: (a) the sensor layout in three different types of pens. (b) installing concealed sensor boxes underneath the flooring.

with a waterproof cable. In the second configuration, we put the sensor inside the waterproof box to better protect it from the elements at the cost of a weaker connection to the structure, which is more durable than the first configuration.

6.1.2 Real-world Evaluation in an Animal Research Farm in the U.S. We deployed *PigSense* for one year at the U.S. Meat Animal Research Center in Nebraska, USA, from January 13th 2021–January 21st, 2022 with five lactation cycles recorded. Data collection was performed in accordance with federal and institutional regulations regarding proper animal care practices and was approved by the U.S. Center for Animal Research Institutional Animal Care and Use Committee as *EO*#143.0.

We installed 15 sensors over three different types of pens, with 5 sensors in each pen. As shown in Figure 21(a), the layout consists of 1 sensor in the middle of the pen to capture the vibration from the sow and 4 sensors at the edge of the pen to measure the vibrations from the piglets. All sensors are concealed in plastic boxes to prevent damage from high-pressure water during cleaning

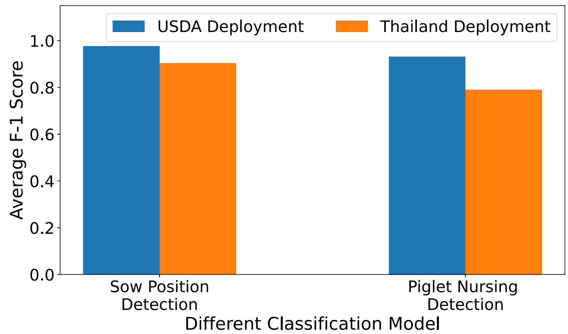

Fig. 22. Results comparison between two different deployments. In general, the performance of our model is consistent across these two sites. Compared with the Thailand deployment, our method achieves a slightly higher accuracy on the data collected from the USDA deployment because of the iterative improvement of the hardware.

and excretion from the sow during operation (see Figure 21(b)). The sensors were all installed underneath the pen, fixed with multiple zip-ties to ensure firm coupling with the floor structure.

For this deployment, we standardized the sensor node design based on our previous experiences. Section 6.3 will detail the iterative design process and lessons learned in more detail. Each sensor was contained within a watertight enclosure, including the geophone inside positioned for intuitive installation below the pen. As the first deployment performed without direct oversight from the sensor engineers due to COVID-19 pandemic restrictions, this deployment tested the remote management and *deployability* aspects of the *PigSense* system.

6.2 Overall Performance

Our swine activity recognition method (described in Section 5) is evaluated with the data collected from two field deployments presented in Section 6.1. Figure 22 shows the overall evaluation results for both deployment sites. From the figure, we observe that the performance of our model is consistent across these two sites, which demonstrates the robustness of *PigSense* in various environmental conditions. Compared with the Thailand deployment, our method achieves a slightly higher accuracy on the data collected from the USDA deployment in the sow position detection and piglet nursing detection model, resulting from the iterative improvement of the hardware (which will be discussed in Section 6.3). In addition, the evaluation performances in these two datasets have relatively high variability for the sow motion detection model, sow motion classification, and people detection model. This is because the distribution of labels is seriously imbalanced for these three models. Take people detection as an example–only about 100 samples whose labels are positive are among nearly 30,000 samples in both datasets. In this case, even though principal components are extracted before training the model, the model's evaluation performance will still be influenced by some processes with randomnesses, such as oversampling for samples whose labels are imbalanced. According to the repeated tests, the difference in the F-1 scores between the results from the USDA and the Thailand deployments was generally no more than 0.1.

6.3 Deployment-informed Iterative Design

Over the course of several deployments, we gathered data that allowed us to steadily improve our hardware, resulting in a robust yet sensitive system that can stand up to its challenging environment while still providing reliable data. Here, we describe our design decisions and lessons learned through multiple deployments.

6.3.1 Environmental Effects. Before our first deployment, we knew that the physical environment of the farrowing pen would provide our sensors with serious environmental challenges. However, it was impossible to fully anticipate how our sensors would handle exposure until deploying and witnessing the environmental damage first-hand. Over several deployments, we found the primary damage sources to be liquid ingress, chemical exposure, and mechanical damage from high-pressure cleaning jets.

Most of the environmental hazards come from the animals themselves or their care. For example, the primary chemical hazards come from animal waste, such as pig urine and excrement. These contain chemicals such as urea and natural acids that damage the seals and casing of our sensors. The liquids from animal waste, drinking water, and the jets used to clean the sewers also frequently drench the area where our sensors are deployed, potentially ingressing the casing. Since our sensors are made of metal and sensitive electronics, they are vulnerable to short circuits from water or degradation from chemical exposure. Thus, the individual sensor nodes needed to be both watertight and chemical-resistant while still maintaining enough sensitivity to accurately track the pigs' movements.

6.3.2 Accounting for Animal Behavior. The pigs' reactions to sensors in their pen dictated the location and power supply constraints. We placed the sensors underneath the floor of the pen to prevent the pigs from disturbing them. After noticing the pigs congregating around the sensor nodes, we realized that we needed to further reduce the attraction of the pigs to the nodes. Thus, we also removed indicator lights where possible and oriented them away from the pigs so only plain plastic was visible through the pen floor.

Powering our sensors was also constrained by animal behavior. Since the time between farrowing and weaning is typically a month or greater, we determined that the sensors needed an external power supply. Wiring the sensors to the building's power supply came with its own challenges, however. In one instance, an escaped pig ran into the power supply module on the wall and pulled the cord, cutting power to two of the sensors. Ironically, in this case, the pig activity that we set out to monitor proved to be our hardware's undoing.

6.3.3 Effects of Sensor Positioning. To further understand the impact of structural variation on the system, we installed multiple sensors under each farrowing pen. We placed two sensors each at five different locations for each rectangular pen, as shown in Figure 20(c). This allowed us to explore and reduce the impacts on the data distribution and examine the effect of having the sensors inside the protective box vs. attached directly to the underside of the floor.

Comparing Sensor Mounting. We found that the sensors inside the box had a somewhat dampened response at frequencies under 100 Hz, but often showed an improved response at frequencies above 100 Hz. We attribute this to the zip-tie connection between the protective box and the floor grating, which may have allowed the box to vibrate more freely than the floor itself while also blocking some of the incoming low-frequency signals. Despite this, we found the sensors in both configurations provided equally useful data in our long-term and short-term algorithms. Thus, in the interest of *deployability* and *physical fault tolerance*, later deployments used only geophones installed inside the protective box.

Comparing Sensor Locations. In all the pens, the highest accuracy for classifying a particular activity depended on the location, not the sensor mounting. However, this location varies with the activity types. In the Thailand deployments, we found that the best sensors for detecting laying were next to the feeder and the water dispenser, while the best sensors for detecting nursing were in the middle. This is likely because nursing usually happened in the middle of the pen, while standing occurred primarily in the feeding and drinking areas. While there were some

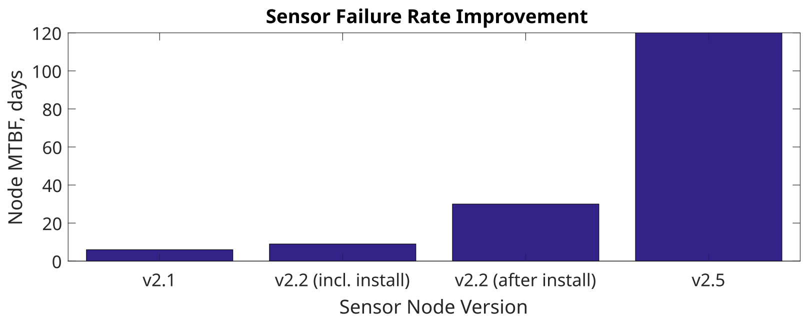

Fig. 23. Mean time between failures (MTBF) for individual nodes across deployments of different hardware revisions. For version 2.2, two bars are shown: one the raw failure rate, and the other after excluding installation-related failures, which were a major unexpected factor in node failures.

discrepancies in this comparison, they came from pens with a different layout and a large number of failed sensors, leaving few locations to compare.

6.3.4 Deployable and Manufacturable Design. For the early deployments in Thailand (see Section 6.1.1), the design focus for the sensor nodes was rapid prototyping. This focus enabled the iterative design process, but eventually, the hand-assembly required counteracted the redundancy desired for *fault tolerance*. Thus, scalability and redundancy demanded a shift to a rapidly constructible sensor node with a relatively stable design.

After several iterations, we found that producing redundant nodes necessitated a shift to a stable, manufacturable design. The prototyping-focused designs were more modular, but this also produced many design variations between deployment iterations. Design stability is needed for more rapid assembly while also enabling *deployability* by those already working in the farm environment. This means, for example, that we standardized the nodes to a single configuration and uniform enclosure. Additionally, the geophone inside is positioned for correct orientation when the intuitive mounting surface is against the underside of the farrowing pen, reducing the likelihood of installation mishaps. Having a consistent design enabled a streamlined installation process that could be carried out with minimal oversight from the sensor designers.

Our final design suggests a framework for designing reliable, manufacturable, and *deployable* sensors. First, the analog signal paths are overdesigned, and specialty components are replaced wherever possible with generic alternatives. This enables both improved manufacturability and improved *deployability* through tolerance to minor orientation and changes. Second, installation steps required at the farm are reduced to a minimum. Fewer installation steps translated directly to less system knowledge required to install a working sensor network. Finally, our sensors can be remotely monitored and managed, allowing the engineers to perform more detailed steps remotely during or soon after installation.

6.3.5 Sensor Reliability Results. We evaluate the reliability of our sensors in the farm environment by tracking the rate of individual sensor node failures. Specifically, we consider the "failed" condition when a node no longer provides any useful data, the same as in our previous work [14]. The results from this evaluation are shown in Figure 23 according to hardware revision.

The revision numbers listed in Figure 23 represent different snapshots of our iterative design process. Version 2.1 is the final iteration deployed in Thailand. While the earlier revisions lost sensors so quickly that they could not monitor an entire farrowing period [10], the final iteration managed an average of six days between node failures. The 2.2 revision was very similar to v2.1 but proved

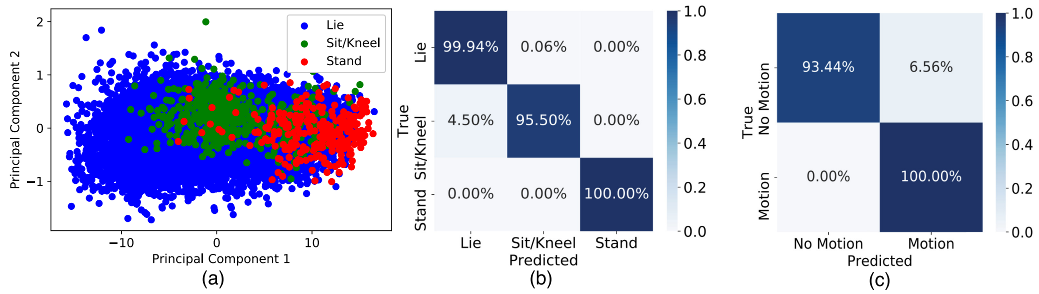

Fig. 24. (a) The first two principal components after PCA show the features are separable among different sow postures. (b) Confusion matrix in predicting lying, sitting/kneeling, and standing postures without label smoothing. (c) Confusion matrix in motion detection.

more robust during the run of the system. This version suffered, however, from many failures related to installation. For the most recent revision, applying the *deployability* principles described in Section 6.3.4 led to nodes that proved more robust to both installation and environmental hazards. In the most recent deployment, only a single sensor failed between both the installation and a full lactation cycle, demonstrating the improvements made to sensor robustness, deployability, and error recovery.

6.4 Results for Sow Posture and Activity Monitoring

In this section, we summarize the results of sow activity recognition, including sow posture and motion prediction (Section 6.4.1) and ingestion and excretion detection (Section 6.4.2).

6.4.1 Prediction of Sow Posture and Detection of Posture Changes.

Sow Posture Classification. *PigSense* achieved 100%, 95.5%, and 90.9% test accuracy in detecting lying, sitting/kneeling, and standing postures, respectively (see Figure 24(b)). As we observed from the figure below, features from different postures are visually separable, observing the first two principal components represented by the x- and y-axis. We found that the first principal component has a basis function that contains mainly the normalized signal energy, which matches the observation that the activity intensity increases significantly as the sow switches from lying to sitting/kneeling and then standing. However, samples from the lying behavior overlap with the sitting/kneeling, as well as standing, leading to misclassifications that bias toward the lying postures (see the first column in the confusion matrix). This may result from the time windows when the sow is standing, sitting, or kneeling without any movements. In this case, it is difficult to tell the sow's posture from the ground vibrations.

To reduce this bias due to the motionless period, a smoothing method over the predictions is applied (as discussed in the method section). Figure 25 shows the ground truth (blue color) and the predictions (yellow color) before and after the smoothing. As observed, the predictions from each window are smoothed by the majority of the adjacent windows, which allows the motionless period to be predicted by nearby time slots with movements.

As a result, the accuracy improved to 99.9%, 99.8%, and 93.7% for lying, sitting/kneeling, and standing postures, respectively, after correcting the bias.

Up and Down Motion Detection. Our method has a 95% F1-score in prediction by inferring the motions from the posture predictions (see Figure 24(c)). The error mainly comes from the predictions in the postures. The accuracy is also affected by the time resolution in sliding windows, because sow motion usually happens within the length of our sliding windows. While we use the

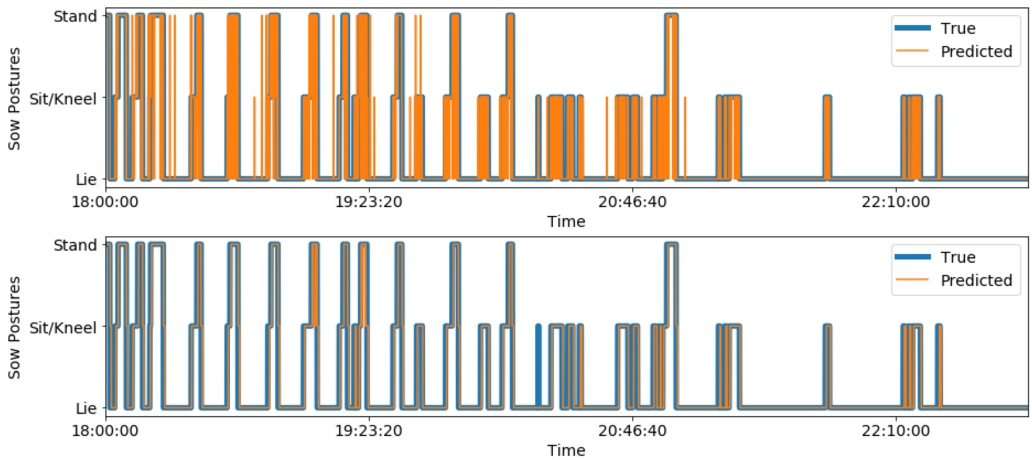

Fig. 25. A representative sample series of sow posture changes **before** and **after** smoothing: The thick blue line indicates the ground truth, and the thin orange line denotes the predictions.

middle time of the adjacent sliding windows to represent the start and the end of the motion, they are not precise enough to approximate the true motion time.

6.4.2 Detection Results for Sow Ingestion and Excretion.

Sow Ingestion Detection. *PigSense* achieved 96% F1-score in sow ingestion. As observed in Figure 26(a), the feature importance plot from the random forest classifier shows that the mean and variance of magnitudes in lower frequency bands are significantly more important in detecting the ingestion activity. This indicates that the ground vibration induced by the sow feeding equipment mainly concentrates in the 0–100 Hz frequency bands. Since eating and drinking have movement rhythms, these bands' variance is also important. Figures 26(c) and (d) show the separable feature patterns of ingestion activities for the sow. Principal component 3 (i.e., the x-axis in the figure) has basis functions mainly contributed by the mean amplitudes over 50–100 Hz. Principal component 9 (i.e., the y-axis in the figure) has basis functions mainly contributed by the variance of frequency amplitudes over 0–50 Hz, which validates our hypothesis that the signal induced by the feeding equipment contributes to the classification performance.

Sow Excretion Detection. *PigSense* has a 71% F1-score in excretion detection. The accuracy is relatively lower than the other activities. This is mainly because when the sow urinates or defecates, the liquid and the solid drops induce significantly lighter vibrations than stepping or hitting the eating tray. Such vibrations are also instant and easily buried by the piglet activities nearby.

6.5 Results for Piglet Activity Monitoring

In piglet group activity classification, *PigSense* achieved 87.7%, 89.4%, and 81.9% F1-scores after smoothing (the same method used in detecting sow activities) in classifying nursing level, sleeping level, and being active level, respectively. The feature selection results show that the three classification models can achieve acceptable accuracy (more than 80%) with less than 30 features (see Figure 27). To achieve the best performance, only 5 features are selected in the nursing level and sleeping level classification model. However, 20 features are selected in the "being active" classification model, because the active state presented the most varied forms of vibration patterns. Figure 28 shows the confusion matrix of the classification results, which will be discussed in the following sections.

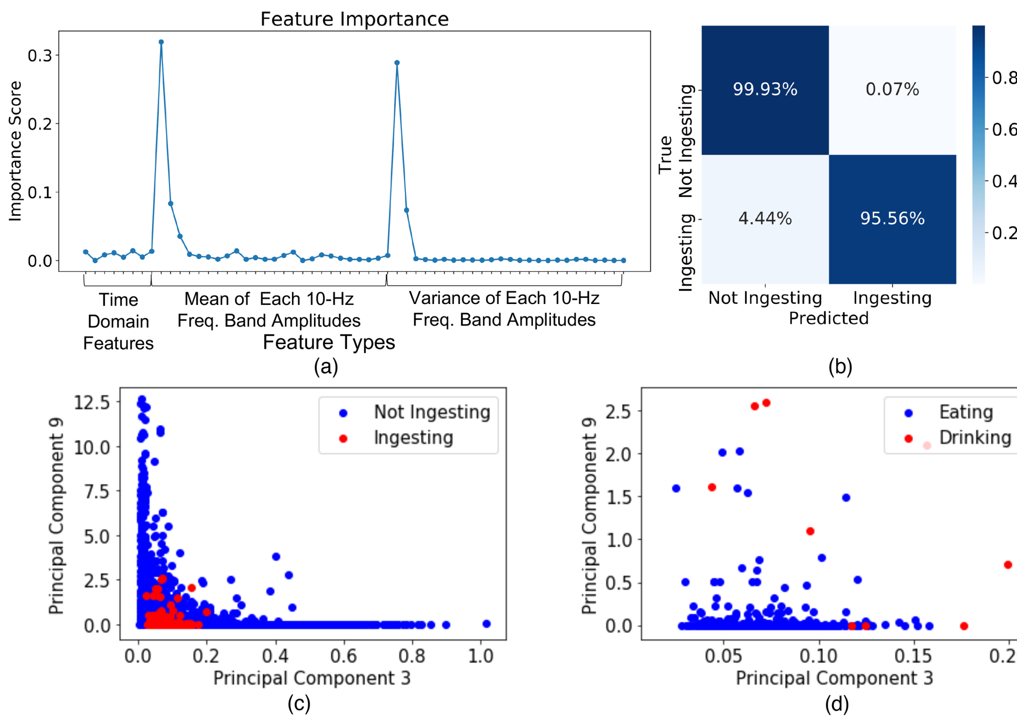

Fig. 26. (a) Feature importance distribution for sow ingestion activity prediction. (b) Confusion matrix of sow ingestion detection. (c) Ingestion vs. no ingestion through 2D visualization of selected principal components. (d) Eating vs. drinking through 2D visualization of selected principal components.

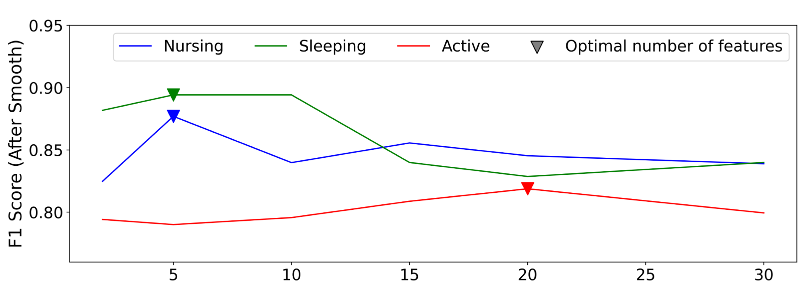

Fig. 27. Feature selection results for piglet group activity level classification. As a whole, the three classification models can achieve acceptable accuracy without too many features. Only 5 features are selected in the nursing level and sleeping level classification model for optimal performance. However, due to the high complexity of the problem, 20 features are selected in the "being active" level classification model.

Piglet Nursing Level Classification. *PigSense* has an 87.7% F1-score for piglet nursing level classification. The five features include three frequency band features (50 Hz, 170 Hz, and 210 Hz) and two local minimal variance features. It could be noted from the confusion matrix that the classification accuracy of the medium nursing level is not as good as other nursing levels. The medium nursing level means all three activities might be somewhat active, which is the most complicated case when classifying group activity levels. The overall good performance of the model mainly comes from the internal regularity of the nursing activity, which is well characterized in the

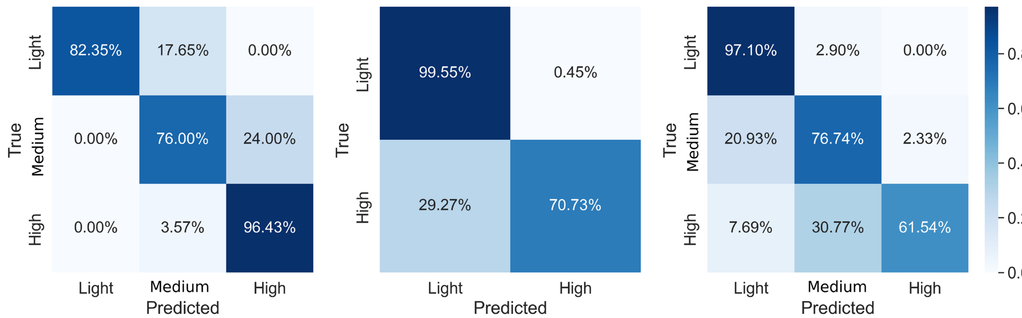

Fig. 28. The confusion matrix of piglet group activity level classification results: (a) nursing, (b) sleeping near the sow, and (c) being active.

frequency domain. While not originally chosen to detect levels of nursing, the local variance features may help quantify the reduced number of peaks in the signal we see when the number of nursing piglets increases (see Figure 18 and Section 5.3.1).

Piglet Sleeping Level Classification. *PigSense* has an 89.4% F1-score for piglet sleeping level classification. The five features include two frequency band features (150 Hz, 170 Hz) and three local minimal variance features. It can be found that the sleeping level is sensitive to some signal features in the high-frequency domain. The local minimal variance in the time domain measures the stability and stillness of a sensor, which plays a vital role in classifying sleeping levels. The relatively good performance of the model is partly because the classification task is binary, which is more straightforward than the other classifiers.

Piglet “Being Active” Level Classification. *PigSense* has an 81.9% F1-score for piglet “being active” level classification. The 20 features include 15 frequency band features ranging from 10 Hz to 170 Hz, 4 local variance features, and 1 signal energy feature. The 20 features also cover all the sensors. This is because piglets can walk, run, or play around anywhere, unlike nursing and sleeping. In this case, all sensors’ vibration data is indispensable for classification. The model does not perform as well as the other two models because, as defined in Section 5.3.1, “being active” includes any activity except nursing and sleeping, such as walking around, running, rolling on the ground, and so on. Three active levels are only an approximate description of these kinds of activities. The varying types of activity included in this category add representation complexity, which is why more features need to be selected in this model. Looking at the confusion matrix, we also see that the classification accuracy of the high “being active” level is lower than other “being active” levels, which is partly subject to the lower number of samples in this class.

The slightly lower accuracy for our piglet activity classification may be partly due to the lower precision of our piglet activity labels, as explained in Section 5.3. However, nursing frequency and duration after labeling with our study were found to be within the expected ranges [2, 43]. Results for piglet group activity classification show the validity of features selected in Section 5.3.1, especially the statistics of frequency bands and local variance in the time domain. It is also worth noting that features extracted from the sensor under sow are essential in all three group activity levels’ classification models, which shows that we can extract piglet-specific features in the midst of vibration caused by sow activity. This is the case when monitoring sleeping and active piglets, as these behaviors are relatively independent of the sow. In the case of nursing, our system also uses vibration information related to sow posture to inform the piglet activity monitoring, as piglets can only nurse when the sow is in the lying position.

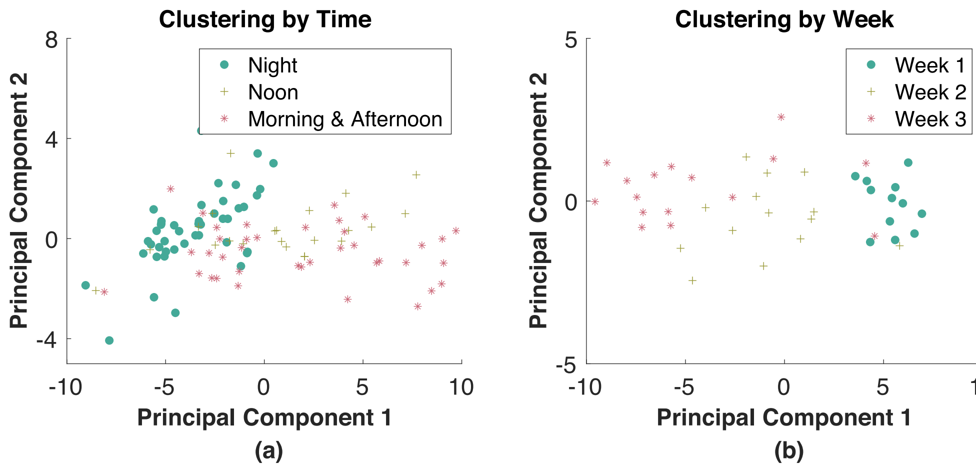

Fig. 29. Cluster visualization using PCA: (a) different time in a day (79.1% test accuracy) (b) different weeks in a lactation period (81.8% test accuracy).

6.6 Results for Piglet Growth Monitoring

The results of piglet growth monitoring include the unsupervised clustering of their behavior patterns and tracking of their weight gain over the lactation period. The behavior patterns are assessed in two different time resolutions, including daily activity patterns and monthly growth patterns. The weight gain is monitored over the entire lactation period and is compared with the signal energy from the vibration data.

6.6.1 Activity and Growth Patterns. For daily and weekly pattern clustering, we focus on the accuracy of every single sensor instead of all sensors. This allows us to be flexible in dropping any sensor that fails during the long-term deployment. To combine different sensor outputs, we select the sensors that maintain connectivity and function throughout the targeted period and plot them in the same figure. As an example, Figure 29 is obtained from sensors 162 and 164 from Pen No. 2, which maintains a good connection and continuous record throughout the cycle.

To prevent our features from biasing towards the outliers, we calculate the 90% quantile, median, and standard deviation of the signal magnitudes in each domain to represent the piglet activity patterns over the lactation period and over each day. To visualize the discrepancy between the clusters, we conduct PCA to compress the feature dimensions into two principal components.

Daily Pattern Prediction. In Figure 29(a), we observe the clusters by plotting principal components to track activity changes during different time slots. To demonstrate that data points with similar features belong to the same cluster, we evaluate the clustering accuracy using **K-nearest neighbors (KNN)**, which gives us 79.1% accuracy for different times of the day. There is a gradual change from active hours (i.e., morning and afternoon) when sow feeding occurs to inactive hours (noon and night) where piglets and the sow are either sleeping or with minor movements. We observe a clear boundary between night and noon, but there are multiple points from morning and afternoon that are mixed into the other two clusters. This is because piglets are not always active during feeding hours. They tend to alternate between walking/running and resting.

Growth Stage Prediction. In Figure 29(b), there are three distinguishable clusters between different growth periods as the piglets go through the three-week lactation period. The KNN model gives 81.8% accuracy in growth stage prediction. From the first week to the third week, the cluster

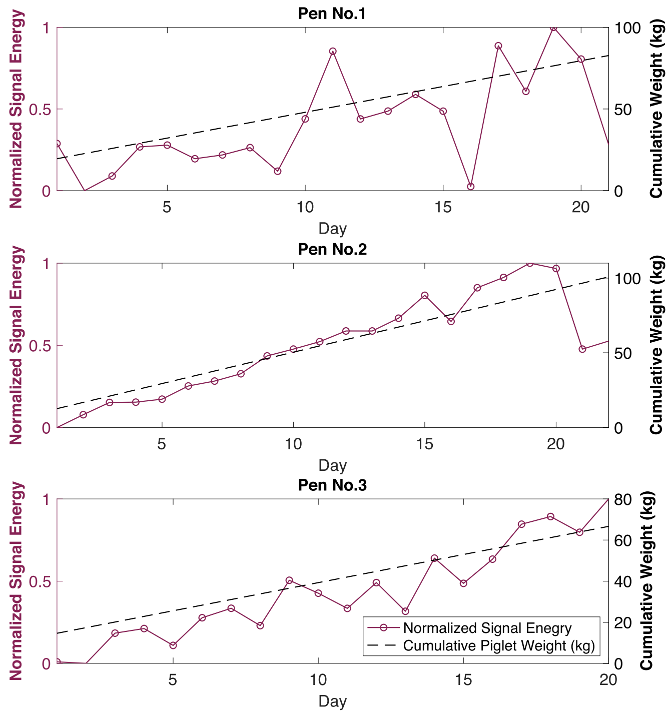

Fig. 30. A representative illustration of the normalized signal energy of a single sensor and piglet weight gain for three pens. The lower correlation for Pen No.1 is due to a connectivity issue with the sensor on day 16, which caused the energy to drop.

moves from right to left, which indicates the gradual growth pattern due to their weight increase and changes in behavior patterns. The results from the clustering provide references for the active time and growth stage of the healthy piglets, which allow us to detect abnormal behaviors that result in feature points that deviate from these clusters.

6.6.2 Weight Gain. For the piglet weight gain analysis, we first obtain the ground truth—overall, the piglets gained an average of 66 kg per pen over the lactation period, which is 5.5 kg per piglet.

We compare the weight gain with the normalized signal energy of a single sensor per pen, as shown in Figure 30. The piglets are weighed at the beginning and the end of the lactation cycle (dashed line). Normalized energy of the vibration signals (solid line) is obtained after each day. The correlation coefficients are 0.62, 0.86, 0.94, respectively. The lower correlation for Pen 1 is due to a connectivity issue with the sensor on day 16, which caused the energy to drop to almost zero. This reinforces our need to accommodate sensor failure. For Pens 2 and 3, there are minor fluctuations in signal energy due to differences in activity intensity across different days.

To prove the correlation relationships statistically, we conduct hypothesis testing mentioned in Section 4.2.1. The p-values are $2.6e^{-3}$, $2.6e^{-7}$, $1.2e^{-9}$, respectively, which are all below the significance level of 0.05. Therefore, we can reject the null hypothesis and conclude that there is a correlation between signal energy and piglet weight gain.

There are variations in the signal energy despite its strong correlation with weight gain. For example, the signal energy varies significantly in Pen No. 1 (the top figure in Figure 30), especially around day 2, day 10, and day 16. This is because the connection of the sensor is not stable on the farm, leading to missing data problems over more than 20 hours on those days. In contrast, the

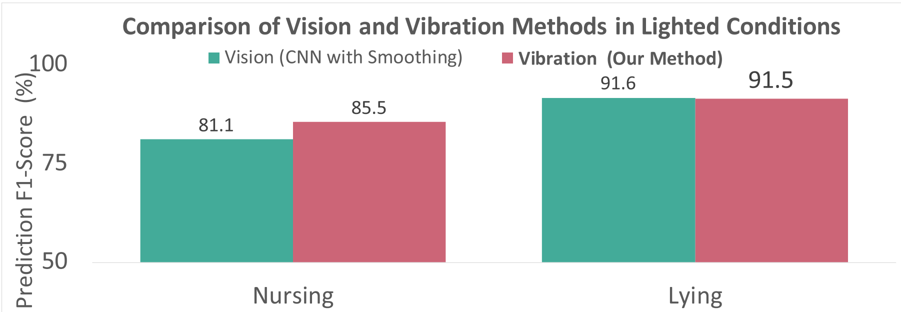

Fig. 31. Results of vision-based vs. structural vibration-based pig activity detection with data from the Thailand deployment. Our structural vibration-based method matches or slightly outperforms the vision-based method in similar conditions.

increasing trend of the signal energy is more obvious in Pen No. 2, resulting from a more stable sensor connection over time. The minor variations in the signal energy can be explained as the day-to-day variations of pig activity levels (see Pen No. 3 in Figure 30). Since the signal energy captures the piglet weight gain indirectly through their activity intensity, the variations in their activity levels due to random events and environmental factors (e.g., human disturbances, changes in weather) lead to variations in the signal energy.

6.7 Comparison with Vision-based Deep Learning Approaches

We compare our structural vibration-based sow lying detection and piglet nursing detection by using an image-based classifier on the data from our first deployment in Lopburi, Thailand. For the image-based classification, we use ResNet18, a deep convolutional neural network pre-trained on the ImageNet dataset [18, 39]. We appended a single fully connected layer to the pre-trained model, which we optimized to our data using cross-entropy loss and stochastic gradient descent, implemented in PyTorch. This is a widely tested industry standard. We trained for 10 epochs with about 5,000 frames of data from a single day. The cross-entropy loss converges to a low value after 6–7 epochs. We debounced the frame-level results with the same sequential smoothing algorithm we used for our vibration analysis and evaluated with data in the same pen.

The results from the vision analysis are compared to our vibration-based method for the same day and pen, as shown in Figure 31. We found that with lying, the algorithms performed equally well, but that our vibration-based method was slightly more adept at classifying nursing. This makes sense, given the difficulty we had manually labeling lying with the cameras: Piglets sleeping next to the sow often look very similar to piglets nursing, and if humans have a hard time distinguishing the difference, then a neural network might have even more trouble.

We also compared the data storage and training times for the two algorithms, which were both implemented in Python on the same computer, with an NVIDIA GeForce RTX 2070 GPU [63]. Table 1 shows the vibration-based analysis requires 12× less storage and 4× training time than the vision-based approach.

It is possible that a future version of either method would work with a lower sample rate (and less data) and could be written to be slightly faster. Even knowing that this is an imprecise metric, it is clear that the vibration sensors take up far less storage and would therefore also require much less bandwidth to send data. A large pig farm may have hundreds of farrowing crates [76]. Constantly monitoring all of these with cameras could become infeasible due to all this data. Using vibrations as opposed to images becomes critical in the remote farm environment where

Table 1. Comparison of Processing Time and Storage Needs for Vision and Vibration-based Methods for One Day in a Single Pen

	Storage (one minute)	Training Time
Vision	12 mb	504 seconds
Vibration	1 mb	125 seconds

The vision method uses a single camera, while the vibration-based method combines four geophones. The vibration sensor data takes up much less storage, which would add up quickly on a big farm with many pens.

unreliable data connections do not provide sufficient bandwidth to upload video for off-site processing [6]. Additionally, when implementing this comparison, we chose a pen in an area that happened to be well-lit even at night. Not all of the pens have good lighting, and choosing to leave the lights on all night could cause the pigs to stress as well as add high electricity costs on a big farm [34].

The vision-based method has the advantage that cameras are less susceptible to the sensing unreliability and varying data distributions we experienced with geophones. While *PigSense* has achieved good fault tolerance to sensing unreliability, we have yet to train and test in different pens. We are optimistic that this issue can be effectively addressed in future work by using transfer learning to adapt the data distributions, as we demonstrated with footsteps in a previous work [57].

7 RELATED WORK

Our related work spans several areas, detailed below. We are the first to do automated monitoring of animals with structural vibration sensors. Therefore, our work is informed both by systems of animal monitoring with other types of sensors and structural vibration-based monitoring of human activities.

7.1 Animal Monitoring with Cyber-physical Systems

Much work has been done on automated animal monitoring with cyber-physical systems, with applications including migratory behavior tracking, behavior analysis and activity recognition of farm animals, animal posture monitoring, and animal estrus detection.

The most common modalities are cameras and wearable sensor systems. Cameras are almost exclusively used to detect activities in indoor domestic livestock environments such as pigs and chickens [47–49, 55, 74, 93]. These computer vision methods often have intense processing and storage requirements, making them difficult to deploy in real-time environments. They function best in well-lit areas, which could disrupt animals' circadian rhythms [34]. They also have line-of-sight restrictions that can hamper their effectiveness when there are a lot of animals or equipment. Wearable sensors have become the research standard in livestock monitoring for tracking cows, pigs, sheep, and wild animals [1, 17, 24, 35, 42, 51, 77, 86, 90, 91, 95].

Wearable sensors are susceptible to being chewed on by animals or damaged by social behaviors. Oliviero et al. use photocell movement sensors and force sensors installed in pen to measure movement and are able to predict farrowing onset [64]. So far, no systems have done automatic detection of nursing.

Previous long-term monitoring tracks environmental conditions, activity level, and reproductive status of the livestock, which provide insights for increasing productivity and reducing loss due to disease and mortality [32, 56].

7.2 Structural Vibration-based Activity Monitoring

Structural vibration-based sensing systems have been used for various indoor activity inferences. The intuition is that the vibration signal that contains the information of the physical interactions at the structural surface (e.g., human or animal movements on the floor) propagates far through a solid medium, which enables non-intrusive sparse sensing [71]. As a result, various applications, including identification [21, 70, 72], localization [59, 60], activity recognition [12, 20, 58, 67–69, 82], and physical conditions [5, 11, 22, 27] have been explored in this direction. However, these prior works mainly focus on indoor human information acquisition, which is often in environments with less noise and hazards than the pig farm, as demonstrated in this work.

7.3 Deployable and Failure-tolerant Sensor Networks

Previous work on failure tolerance for sensor networks focuses on self-organizing and -recovering networks [38]. These efforts are important for deployment at scale, though *PigSense* does not yet need such efforts. Additionally, since our sensor nodes are wired for power and organized by farrowing pen, it is unlikely that automatic network reorganization will benefit this specific application.

Redundancy is a well-known technique for improving sensor system reliability. Past work has concretely defined this benefit in terms of optimality conditions [40, 80]. For future large-scale deployments, we could apply these principles to find the minimum number of sensors to achieve a particular reliability constraint if cost becomes a concern [80]. The simplicity of our sensor nodes and the uniformity of their design already help to obviate this issue in our current design.

Deployability by nonengineers is a known but often overlooked challenge in sensor networks [3, 29]. The principles that contribute to deployability or installability are the same as those used in designing personal computer products for non-technical consumers [15]. We apply these same principles of reduced installation steps and uniform fixtures [15] combined with a tiered network organization [29] to achieve our deployability goal.

8 FUTURE WORK

For future work, we plan to extend our study in a few directions, including (1) swine lameness assessment, (2) swine vital monitoring, and (3) cross-modality sensor fusion for swine monitoring.

- **Swine Lameness Assessment:** The Common Swine Audit identified sow lameness as a significant welfare issue in commercial swine production [66]. In existing studies, kinetics and kinematics have been widely used in horses and cattle [37, 62]. Vibration sensors have been shown to be effective in detecting gait abnormalities in patients with muscular dystrophy and measuring human gait balances [23, 26]. Given the research gap, we plan to assess swine lameness using vibration sensors to achieve early detection and discovery of the disease.
- **Swine Vital Monitoring:** Swine heart rate and respiration rate are important indicators of stressful events the sow encounters, as well as the onset of farrowing [54, 81]. During our deployment in this study, our sensors detect periodic impulses as the sow is lying on the floor, which has similar rates corresponding to the heart rate and the respiratory rate. We plan to verify this observation through ground truth measurements of the swine vitals and develop a system that captures such information for accurate stress and farrowing events prediction.
- **Cross-modality Sensor Fusion for Swine Monitoring:** In addition to the floor vibration sensing, other modalities such as computer vision and wearables are also demonstrated as feasible in swine monitoring [45, 52, 96]. We plan to advance our monitoring system by exploiting the advantages of different modalities and developing an integrated system that captures swine behaviors from different perspectives.

Moreover, we aspire to extend our study to different farm livestock, including cattle, sheep, horses, and so on, to improve animal welfare and productivity in the intelligent animal farming industry.

9 CONCLUSION

In conclusion, we introduced *PigSense*, the first system to use structural vibration to monitor animal behavior and the first system for automated characterization of piglet group activities, including nursing, sleeping, and active periods. *PigSense* is non-intrusive to the animals and requires much less processing and storage power than non-vibration-based monitoring systems such as audio- or video-based systems. Our approach relies on the idea that animal activity such as walking and nursing movements creates unique vibration patterns in the structure of holding pens. Our challenges when developing *PigSense* included withstanding a difficult environment for electronics, which often resulted in hardware malfunction and unpredictable noise. We addressed this in Section 3 with multiple simple, durable sensors that can provide redundant information in case of failure. We shared our experiences developing this system in a new farming environment where visitation was severely restricted due to the global pandemic, necessitating a simple and easily maintainable installation that can be deployed by locals on the ground and monitored from afar. Another challenge of our system was in distinguishing behaviors that cause very similar vibrations and may happen concurrently. We addressed this in Sections 4 and 5 by supplementing a general feature extraction process that can detect a variety of different vibrations with the use of domain knowledge to precisely detect certain activities.

We provided an extensive evaluation for activity recognition of a comprehensive list of sow and piglet behaviors in two six-month field deployments at pig farms in Lopburi, Thailand, and Nebraska, USA. *PigSense* recognized six categories of sow behavior, with an average classification accuracy of 90%. For posture and movement classification between lying, sitting, standing, and transitional periods, *PigSense* achieves an average classification accuracy of 96% and an average of 96% and 71% for ingestion and excretion detection. These categories can help assess the risk of crushing, farrowing sicknesses, and the impact on piglets of the sow's maternal behaviors. In addition, we show that our monitoring of signal energy changes in the structural vibration signal allows for the detection of farrowing onset a day in advance due to the changes in vibration caused by the sow's nesting behaviors, as well as timely status tracking during the farrowing process. *PigSense* also recognizes several categories of piglet litter behavior, including three levels of nursing, sleeping, and active periods, with an average classification accuracy of 87.7%, 89.4%, and 81.9%, respectively, which help farmers monitor piglet feeding, risk of starvation, and signs of possible illness. Furthermore, *PigSense* also predicts the daily pattern and weight gain in the lactation cycle with 89% accuracy, a metric that can be used to monitor the piglets' growth progress over the lactation cycle.

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