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Machine learning based fog computing assisted data-driven approach for early lameness detection in dairy cattle

Mohit Taneja[a,b,*], John Byabazaire[a,b], Nikita Jalodia[a,b], Alan Davy[a,b], Cristian Olariu[c], Paul Malone[a]

[a] Emerging Networks Laboratory, Telecommunications Software and Systems Group, Department of Computing and Mathematics, School of Science and Computing, Waterford Institute of Technology, Waterford, Ireland
[b] CONNECT- Centre for Future Networks and Communications, Dublin, Ireland
[c] Innovation Exchange, Dublin, IBM, Ireland

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ABSTRACT

Timely lameness detection is one of the major and costliest health problems in dairy cattle that farmers and practitioners haven't yet solved adequately. The primary reason behind this is the high initial setup costs, complex equipment and lack of multi-vendor interoperability in currently available solutions. On the other hand, human observation based solutions relying on visual inspections are prone to late detection with possible human error, and are not scalable. This poses a concern with increasing herd sizes, as prolonged or undetected lameness severely compromises cows' health and welfare, and ultimately affects the milk productivity of the farm. To tackle this, we have developed an end-to-end IoT application that leverages advanced machine learning and data analytics techniques to monitor the cattle in real-time and identify lame cattle at an early stage.

The proposed approach has been validated on a real world smart dairy farm setup consisting of a dairy herd of 150 cows in Waterford, Ireland. Using long-range pedometers specifically designed for use in dairy cattle, we monitor the activity of each cow in the herd. The accelerometric data from these sensors is aggregated at the fog node to form a time series of behavioral activities, which are further analyzed in the cloud. Our hybrid clustering and classification model identifies each cow as either Active, Normal or Dormant, and further, Lame or Non-Lame. The detected lameness anomalies are further sent to farmer's mobile device by way of push notifications. The results indicate that we can detect lameness 3 days before it can be visually captured by the farmer with an overall accuracy of 87%. This means that the animal can either be isolated or treated immediately to avoid any further effects of lameness. Moreover, with fog based computational assistance in the setup, we see an 84% reduction in amount of data transferred to the cloud as compared to the conventional cloud based approach.

1. Introduction

Internet of things (IoT), fog computing, cloud computing and data driven techniques together offer a great opportunity for verticals such as the dairy industry to increase productivity by getting actionable insights to improve farming practices, thereby increasing efficiency and yield. There has been active initiation and movement in the agricultural domain to move towards tech-enabled smart solutions to improve farming practices, and increase productivity and yield. The concept of Smart Dairy Farming is no longer just a futuristic concept, and has started to materialize as different fields such as machine learning have found a practical applications in this domain.

Timely detection of lameness is a big problem in the dairy industry which farmers are not yet able to adequately solve. It is one of the factors for reduced performance on many dairy farms, at least through reduced reproductive efficiency, milk production and increased culling (Chapinal et al., 2009). Lameness is considered to be the third disease of economic importance in dairy cows after reduced fertility and mastitis (Van Nuffel et al., 2015). An all-encompassing definition of lameness includes any abnormality which causes a cow to change the way that she walks, and can be caused by a range of foot and leg conditions, themselves caused by disease, management or environmental factors (AHDB, 2016). Prevention, early detection and treatment of lameness is therefore important to reduce these negative effects of lameness in

* Corresponding author.
E-mail addresses: mtaneja@tssg.org (M. Taneja), byabazairej@gmail.com (J. Byabazaire), njalodia@tssg.org (N. Jalodia), adavy@tssg.org (A. Davy), rioderaca@gmail.com (C. Olariu), pmalone@tssg.org (P. Malone).

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dairy cows (Alsaaod et al., 2015; Poursaberi et al., 2011). Early detection of disease allows farmers to intervene earlier, leading to prevention of antibiotic administration and improvement in the milk yield, and savings on veterinary treatment for their herd.

With the increasing global demands of agricultural and dairy produce, the scale of farming and livestock management is only set to increase. To increase the productivity on a dairy farm, farmers generally look towards the following two:

1. Control welfare related issues like lameness
2. Increase the number of accurate estrus detection, so as to increase the size of the herd for further profitability.

The latter has been adequately addressed. In fact, there are major industry partnerships like Fujitsu partnering with Microsoft to provide a SaaS (Software as a Service) for accurate estrus detection powered by Microsoft's Azure and Analytics (Meet the connected cow; Hadoop, 2015). So, the next major problem to be solved in smart dairy farming is the ability to accurately and timely detection of lameness.

Our work is motivated by the following facts:

- Manual human observation based solutions for lameness detection are susceptible to human error and are not scalable as the size of the farm increases.
- Few of the existing solutions (discussed in the next section) require the equipment in use for detection to be placed in a controlled position, and the cows need to be constrained to walk through them.

Guiding the cows to walk in a controlled manner and presence of a human being leads to bias in the measurement because of stoic nature of cows; as they will try to hide their weakness and pain compared to measurements made during normal routine without the presence of a human.

Although there are existing wearable sensor based cloud centric and isolated offline solutions, they suffer from the issue of multi-vendor interoperability and vendor-lock in, which has been detailed in the next section. Therefore, there is still a need for further automation and advanced machine learning based solution that:

- Monitors the animals everywhere they are – either in the fields grazing, during milking, or lying down in the shed.
- Is Population Agnostic – takes into account individual animal behaviour.
- Is Environment Agnostic – takes into account variations in weather and environment.

In this article, we present an end-to-end IoT application that leverages threshold based clustering and machine learning classification to detect lameness in dairy cattle. The application automatically measures and gathers activity data (lying time, step count and swaps per hour) continuously, so that cows can be monitored daily. Furthermore, the clustering technique employed ensures that the models dynamically adjust depending on farm and weather conditions, and automatically selects a custom learning model for that cluster.

Our contribution and core novelty of the work presented is summarized as follows:

1. Although the existence of clusters in herds have been used before in cattle behaviours (Stephenson and Bailey, 2017), this study is the first to use cluster specific model for lameness detection as opposed to a one-size-fits-all solution.
2. The technique used to form animal profiles eliminates the effects of external factors like weather, location and farm conditions. This study is the first to offer an early lameness detection service that is population and environment agnostic.
3. The study is the first to propose a feedback based re-training based on the inputs of the human in the loop, who could be an agricultural expert or farmer.
4. The study is amongst one of the few to apply modern AI (Artificial Intelligence) techniques to detect lameness in dairy cattle.
5. The methods are deployed in practice and real data has been collected. The proposed approach has been validated in a real-world IoT deployment in a Smart Dairy farm setup with a full herd of 150 dairy cows.

The paper has been further structured as follows: 2 presents the literature review, background, state-of-the-art and motivation, 3 presents the experimental setup, system architecture and application design, 4 presents materials, methods and machine learning model developed, 5 presents discussion of the results, and finally 6 and 7 present the conclusion, Ongoing and future work respectively.

2. Literature Review, background and motivation

2.1. Lameness in dairy cattle: geographical variance and associated costs

The prevalence of lameness has been reported differently in different regions and states. Ger reported that on an average Irish farm, 20 in every 100 cows will be affected by lameness in a given year. In the United States authors in (Cook, 2003) and (Espejo et al., 2006) reported a mean lameness prevalence of 25%, whereas in California and the northeastern United States, overall lameness prevalence was estimated to be 34% and 63%, respectively (von Keyserlingk et al., 2012). British and German studies reported a lameness prevalence of 37% and 48% (Whay et al., 2003; Barker et al., 2010), whereas a prevalence of 16% was reported in the Netherlands (Amory et al., 2006). In our experimental deployment on a herd of 150 cows in Ireland, 26 cases of lameness were recorded during July to December 2017. Further up by the end of the experiment in April 2018, a total of 32 cases were recorded overall.

Lameness can be classified into three main categories: solar ulcers, digital disease (white line abscess, foreign bodies in the sole, and pricked or punctured sole), and inter digital disease (lesions of the skin between claws and heel including foul in the foot, inter digital fibroma and dermatitis). More than 65% of cases of lameness are said to be caused by diseases (Foditsch et al., 2016). Other causes include injuries to the upper skeleton or major muscles, septic joints and injection site lesions.

Lameness has many negative effects, including reduction in feed intake, reduction in milk production (mainly due to withdrawal due to antibiotics usage) and weight loss. It therefore has a drastic effect on the performance of a dairy farm. Lameness is mostly detected at advanced stage and thus requires immediate and often costly treatment. Once an animal becomes lame, it can take several weeks to recover. Lameness thus represents a significant cost to dairy farmers in terms of time, financial expenditure for veterinary calls, medication and treatment, and also for loss in production. Table 1 (Ger) summarizes the costs estimates for each type of lameness.

2.2. Existing approaches for lameness detection

2.2.1. Pressure plate/load cell

In these solutions, the main aim is to investigate how the weight is

Table 1
Costs associated with each type of lameness.

Type of lameness	Digital	Inter digital	Solar ulcer	Average case
Prevalence (%)	45	35	20	
Total cost of a single case (in €)	282.85	136.12	504.58	275.26

distributed across the legs of the animal as it walks through a marked area. Neveux et al. (2006) studied the use of a platform outside the automatic milking system to measure the weight distribution of cows while standing on different surfaces. Chapinal et al. (2010) and Pastell et al. (2010) later adjusted the experimental setup to measure lameness and hoof lesions.

The drawbacks of such solutions may not be only the costs of new and complex equipment but also other technical concerns. For example, Pastell et al. (2010) suggested that a cow may suffer pain when walking, which is not as obvious when the cow is standing still. In this setup, the cow must be guided or must be standing in controlled position. Because cows are stoic in nature, this will affect the measurements and alter the results.

2.2.2. Image processing techniques

This category studies the use of image processing techniques to analyse the posture of the animal as it walks through a milking parlour. Poursaberi et al. (2010) proposed a method based on detecting the arc of back posture and fitting a circle through selected points on the spine line of a cow as it walks. Viazzi et al. (2013) further studied the idea and an algorithm based on Body Movement Pattern was tested under farm conditions. Further study on this method shows that there remain challenges on real farm conditions. For example, changing lighting conditions cause noise and shadows in the images that impede extraction of the back posture, or continuous background changes that interfere with cow segmentation from the images. Some of these challenges were explored by Poursaberi et al. (2009), Van Hertem et al. (2013) and Viazzi et al. (2014).

2.2.3. Activity based techniques

Here, techniques use accelerometers (2D and 3D) and pedometers to record movement patterns of the animal. This data is then used to build the daily activities of the cow, e.g. walking, lying down. Munksgaard et al. (2006) proposed the use of sensors that measure acceleration in different dimensions to automatically monitor activity (standing and lying behaviour) of cows. Their results indicate excellent accuracy between the sensor data attached to the legs of the cows and observations for lying and standing (0.99), activity (0.89), and number of steps (0.84). Chapinal et al. (2011) used five 3D accelerometers on cows, one on each limb, and concluded a single device attached to one of the legs appeared to be sufficient to measure the walking speed of cows, which was associated with locomotion scores. In other studies accelerometers were mounted on a hind leg of 348 cows in 401 lactations on four commercial farms (Thorup et al., 2015). Since then, a vast number of studies have used accelerometers to measure dairy cow activity and behaviour (Alsaaod et al., 2012; Yunta et al., 2012; O'Driscoll et al., 2008; Blackie et al., 2011).

2.3. IoT, fog computing and data analytics in agriculture domain

There have been proposed systems in industry (Ag, 2017; Ireland, 2017; Boumatic, 2017) as well in academia (Taylor et al., 2013; Chen et al., 2014; Wark et al., 2009; Brewster et al., 2017) for animal health management in dairy farms. Authors in (Al-Fuqaha et al., 2015) provide a detailed survey of IoT enabling technologies that can offer automation, data aggregation and protocol adaptation in the wide field of IoT. They also present the required integration of IoT with emerging technologies such as data analytics and fog computing. Another survey in (Rutten et al., 2013) identifies a serious lack of analytics and intelligence in existing smart dairy farming systems, thus leading to gaps between the desired requirement of the system and proposed solutions. It articulates the pressing requirement of intelligence to be present on the premises, in the on-farm systems. As a consequence, attention is being drawn towards designing systems with intelligence and data analytics capability being present on premises (Shi et al., 2016), and utilizing fog computing comes to shore with those objectives in mind.

Authors in (Muangprathub et al., 2019) present the need of data driven movement in agriculture in order to improve crop yields, improve quality, and reduce costs. Another recent survey by authors in (Jukan et al., 2017) identifies the lack of interoperability provided by such systems, and the need of developing an integrated system combining edge, fog and cloud to provide application and services. The authors here also identify that technology solutions with no consideration of interoperability results in vendor lock-in, which not only hinders innovation, but also results in higher costs for the farmer/user.

Authors in (Caria et al., 2017) present the use of Raspberry Pis as edge devices which are further connected with the cloud to demonstrate a smart farm computing systems for animal welfare monitoring. Authors demonstrated that a low-cost and open computing and sensing system can effectively monitor multiple parameters related to animal welfare. While animal welfare remains a broad concept, their paper shows that many parameters relevant to various stakeholders can be measured, collected, evaluated and shared, opening up new possibilities to improve animal welfare and foster high-tech innovations in this sector.

The authors in (Hsu et al., 2018) propose the use of fog computing for innovative service creations for existing cloud based agriculture system. By means of simulation, the authors demonstrate that fog computing presents a unique capability for a creative IoT platform adoption in agriculture with existing cloud support. Quite recently, authors in (Zamora-Izquierdo and Santa, 2019) describe the design, development and evaluation of a system that covers extreme precision agriculture requirements by using automation, IoT technologies, and edge and cloud computing through virtualisation.

2.4. How is the proposed system novel as compared to the existing ones?

Although most farms are equipped with some kind of estrus detection system (Miiaková et al., 2018) which is based on accelerometers, lameness detection systems based on the same have not been successful. This is because of vendor lock-in. Each of the system would require its own hardware. Worth mentioning is the insight in the review by Van De Gucht et al. (2017) that farmers who already had an estrus detection system were willing to have an add-on for lameness detection. All the current systems lack this kind of integration. Another assumption made by all the current solutions is that all the animals will get lame the same way. To put this into context, consider a farm in Ireland – there are two main seasons, summer and winter. During summer, the animals stay in the field and graze freely, while during the winter the animals are kept in house. In both cases the activity levels of the animals are different. Interestingly, as the activity levels are low during winter considering the animals stay indoors rather than having much outdoor activity, the entire herd's activity pattern will be closer to that of a lame animal during the summer. Therefore, a learning model should be able to consider such external factors.

In a review by authors in (Van Nuffel et al., 2015) about automatic lameness detection, some suggestions were made. One of these was the need for automatic and continuous measurement of the parameters. This is because most solutions available require the animals to be guided one way or another. The other suggestion was the need for custom solutions, systems that need less space or those that can be included in the existing farm infrastructure (Van Nuffel et al., 2015).

The presented work differs from the existing sensor based system solutions by offering following advantages:

- Sensor agnostic: The model is built to take in activity data from any kind of sensor used to monitor activity of the animal. This among other thing will reduce the initial installation costs if a farm already has a system in place.
- Avoids vendor lock-in: Design, creation and development of services following a microservices based application design principles to tackle the problem of vendor lock-in and to support multi-vendor

interoperability.

- Multiple end-users: Since our system is designed as a service, this makes it easy to integrate with the existing systems. The end user therefore could be a farmer with an existing system or even an agri-tech service provider who wants to provide more services to their clients.

One of the primary limitations of the previously proposed systems is that they follow the technique to process and analyse previously collected data and perform only cloud based analytics without leveraging and efficiently utilizing the resources (Taneja and Davy, 2016) available on the farm along the things-to-cloud continuum (Taneja and Davy, 2017), moreover such techniques are not always suitable for real-time tracking and monitoring of dynamic entities such as dairy cows. The gaps with the existing research is that either it has been developed out of the agricultural context, or addresses the issue of analytics and control in isolation; this has also been identified as key limitations by authors in (Zheleva et al., 2017).

While there has been a movement towards data-driven agriculture in recent times for sustainable and productive growth, there is still a void when it comes to leveraging emerging paradigms such as fog computing, and applying innovating machine learning models to solve a specific problem in the dairy sector. Most of the articles in literature present results based on simulated experiments, and those which come from real world deployment are mostly agriculture based, and rarely based on dairy farming. Further, only some of them have a machine learning element to automate their approach. However, to the best of our knowledge, no prior work focuses on providing an end-to-end IoT solution integrating edge, fog and cloud intelligence specifically in case of smart dairy farming IoT settings.

We position our work as an answer to the issues mentioned above, thus bridging the gap, and providing an innovative way that integrates edge, fog, cloud computing and machine learning to provide a solution specifically in case of smart dairy farming in an IoT setup. The novelty of the proposed model comes from the standpoint that it has been specifically designed and developed to address a specific vertical of the IoT ecosystem i.e., dairy farming, and within that to address a specific problem related to animal welfare i.e., detecting lameness at an early stage before the clinical signs of it appear, with a microservices oriented design making it multi-vendor interoperable.

3. Experimental setup – smart dairy farm setup: real world test-bed deployment

As part of the experiment, the trial[1] was conducted on a local dairy farm with a full dairy herd of 150 cows in Waterford, Ireland. Amongst the available options for the sensors/wearables available for livestock monitoring, we used commercially available radio based Long Range Pedometer (433 MHz, ISM band, LRP — ENGS Systems©®, Israel) in our deployment. These pedometers were attached to the front leg of cows in the herd, as shown in Fig. 1.

Fig. 1. Long Range Pedometer (LRP) attached as a part of the experiment to the front leg of the cows.

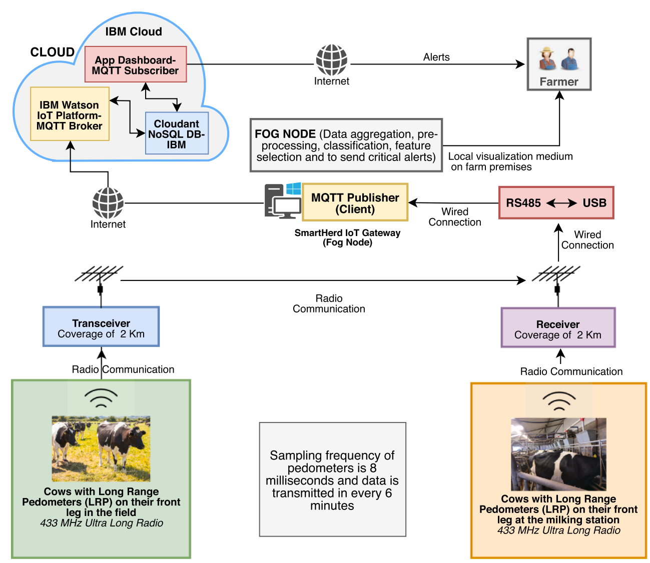


Fig. 2. Overall architecture of the test-bed and system overview.

3.1. Architecture design and system overview

The overall architecture of the test-bed is shown in Fig. 2. As shown in Fig. 2, the Receiver is the master unit which sends the received data to the communication unit (RS485 to USB) through wired connection, which in turn then sends it to the gateway (a PC form factor device in our case, which acts as controller and fog node. The configuration[2] used is Intel® Core™ 3rd Generation i7-3540 M CPU @ 3.00 GHz, 16.0 GB RAM, 500 GB Local Storage) through wired connection via USB interface. The fog node consists of a local database which stores all the data from the sensors before it is preprocessed. The collected raw data is then preprocessed and aggregated at fog node to form behavioural activities, and summed to form daily time series. In this study, we used three behavioural activities (step count, lying time, swaps) for the analysis with their description below:

1. *Step count:* This is the number of steps an animal makes.

[1] The ethical approval for the experimentation was taken from Research Ethics Committee of Waterford Institute of Technology, Ireland prior to the deployment in July 2017.

[2] Note that our results presented in Taneja et al. (2019a) suggest that the system is fully capable to run with fog node of lower computational power without compromising on quality of service. The results on resource utilization at fog node and discussion on platform performance on using fog node with low level computational power, and system resilience has been discussed in greater detail in our work available at Taneja et al. (2019a).

2. *Lying time:* The number of hours an animal spends lying down.
3. *Swaps:* This is the number of times an animal moves from lying down to standing up.

We used Message Queue Telemetry Transport (MQTT) (MQTT, 2017) as the connectivity protocol between fog node and cloud (service instances running on IBM Cloud) in our deployment setting. MQTT is an open-source protocol originally invented and developed by IBM (Getting to know MQTT, 2017). It is a lightweight publish-subscriber model based protocol designed on top of the TCP/IP stack. It is specifically targeted for remote location connectivity with characteristically unreliable network environments such as high delays and low bandwidth (Lee and Kim, 2013), which is one of the issues in remote farm based deployments such as ours. Hence, we chose MQTT as the connectivity protocol in our deployment.

The MQTT architecture comprises of two functional components, namely MQTT clients (such as publishers and subscribers) and MQTT broker (for mediating messages between publishers and subscribers). In our setup these components are as follows:

- **MQTT Publisher:** Script running on fog node (i.e., local PC at farm)
- **MQTT Broker:** IBM Watson IoT Platform (as a service on IBM Cloud)
- **MQTT Subscriber:** Application designed and hosted on IBM Cloud

Thus, the data from fog node after pre-processing, aggregation and classification as described above and shown in Figs. 2 and 3 is streamed to IBM Waston IoT platform using MQTT, the IBM Watson IoT platform receives all these messages, and the MQTT subscriber listening to the events of this broker picks up all the data and stores it in Cloudant NoSQL JSON Database at IBM Cloud.

3.2. Designing and developing an IoT based software system: objectives and challenges

Building an IoT application is an intricate process involving end-to-end components, each of which is adapted to the use case being addressed. Generally speaking, an end-to-end IoT solution towards a smart scenario involves the following steps:

- **Connecting the Unconnected:** This step involves the installation of sensors on physical entities such as objects (both static or in motion), remote infrastructure or living entities towards achieving a specified objective such as monitoring.
- **Data Acquisition:** This involves attaining the sensor data and transferring it to the data analytics platform(s) to achieve actionable insights for better decision making. This becomes a critical problem in scenarios such as ours, wherein a farm location has little or no Internet connectivity.
- **Architecting, Integrating and Management:** This crucial phase involves key decisions on the software architecture and design principles to be used during development of the system. Once finalized, the next step is to integrate, optimize and manage the computing system thus built, which is usually an ongoing process.
- **Data Analytics:** Once the data is at the desired platform (be it fog or cloud), this part involves figuring out how to analyze the data to get the desired information to achieve the specified objective, given the constraints.

We also had the same objectives in mind while developing the application in our scenario, the first three of these objectives have been explained above and further below in this section, and the data analytics objective has been explained in greater detail in the next section.

The end-to-end data and work flow of the developed application has been presented in Fig. 3. The primary challenge is to design an end to end IoT solution to meet the specified objective given the highly variable, harsh and resource constrained environment in a smart dairy farming setting. This includes making the system resilient and fault tolerant to cope up with the variable farm environments, including weather-based network outages and connectivity issues because of remote location of the farm. A detailed discussion on test-bed deployment challenges, technical challenges faced during deployment and development, and critical decisions made, was presented in Taneja et al. (2019b).

The use of fog computing brings efficiency and sustainability to the overall IoT solution being proposed. In most cases, farms are located in remote locations and can suffer from phases of low or no Internet/network connectivity. In such adverse connectivity scenarios it becomes ideal to process the data locally as much as possible and send the aggregated or partial outputs over the internet to the cloud for further enhanced analytical results. In view of this we design our solution utilizing fog computing which aims to bring computation capabilities closer to the source of data. The fog computing based approach leads to effective utilization of limited available resources (Taneja and Davy, 2017) and also leads to significant reduction in the amount of the data being transferred to the cloud.

3.3. Offline-first model for mobile application design

Farms are usually located in geographically remote locations facing constrained network connectivity. Most of the IoT deployments in such settings are faced with limited cellular coverage. Existing solutions are mostly cloud based or completely offline. This limits the farmers' ability to interact with the application anytime and anywhere. The system developed in this study has an offline enabled strategy via the mobile application and cloud dashboard. Fig. 4 shows the data flow of the offline enabled design approach.

Once the model produces notifications, these are sent to the farmer's mobile device as push notifications. On board the application is a PouchDB (Pouch, 2019) database which synchronizes with the cloudant database in IBM cloud using a REST API whenever a connection is established. The application in general helps to achieve the following tasks:

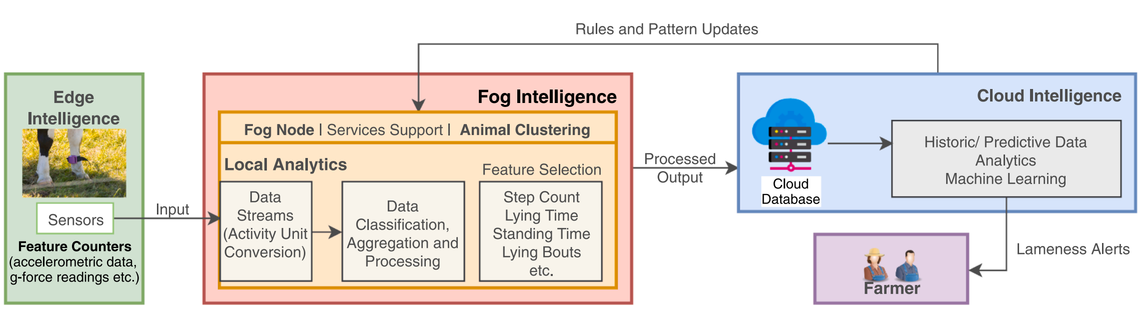


Fig. 3. Work flow and data flow in the test-bed deployment.

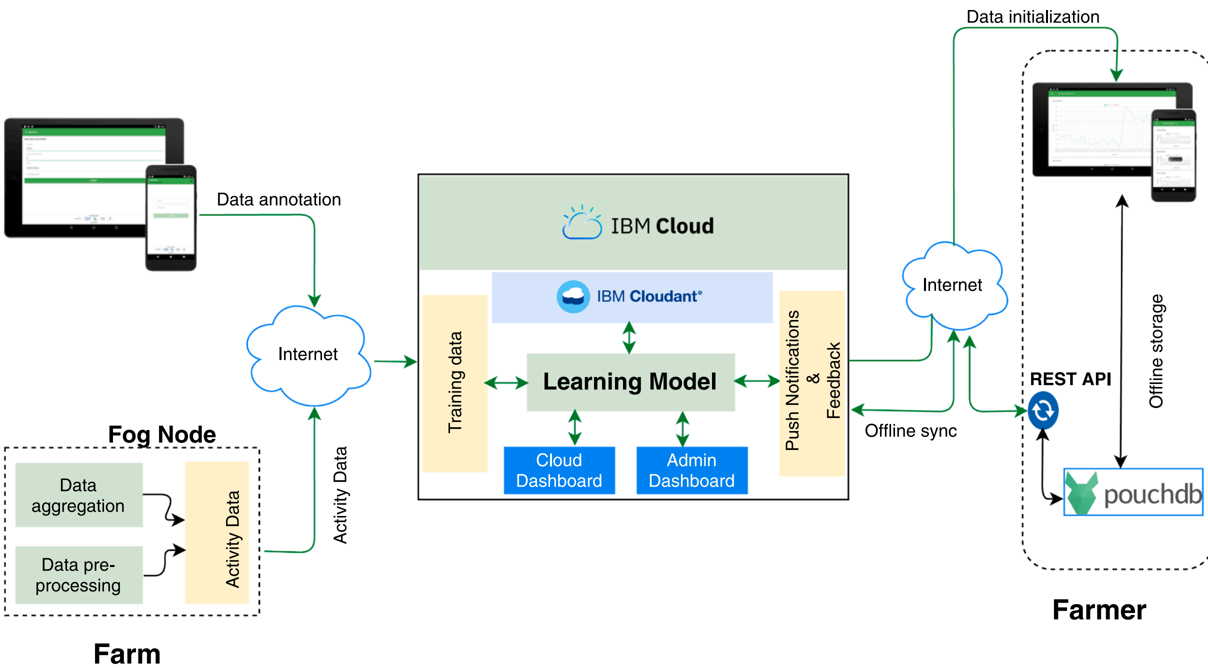


Fig. 4. Mobile application developed specifically considering the needs of the farmer, including an offline first strategy. The figure presents data and notification flow in the developed mobile application.

- Push notifications: Whether on WiFi or limited cellular network, or whether the application is open or not, these will go through each time the status of the farm changes.
- Data annotation: During the training process, this feature was used by the human operator to annotate the data. In our case, this was done weekly by an agricultural science student.
- Feedback to improve model learning: When a notification is generated, the farmer has the option of confirming if the identified cow is actually lame, or tag it as a false alarm or even report a missed alert. All this information is sent back to the model to improve its accuracy.

3.4. Microservices based application flow for multi-vendor interoperability

Unlike the existing systems that are based on a monolithic design approach, the application designed in this study follows a microservices (Balalaie et al., 2016) based approach for design, creation and deployment. The aim is to make the developed system as Application/Software as a Service', which can be used by the service providers to integrate with their existing systems. For example, an agri-tech company could be a service provider for any other solution such as mastitis detection, who wants to expand their system or integrate any of the services such as lameness or heat detection into their system. A visual representation of such a possible integration is presented in the Fig. 5. Feature engineering layer as shown in the Fig. 5 ensures that data is transformed to output only the required features and also reject those that cannot be engineered to form the required features for a desired service; for example Lameness Detection and Heat Detection Service expects lying time, step count and swaps but a service provider might have activity counter instead of step count and (Stand up + Liedown) instead of swaps.

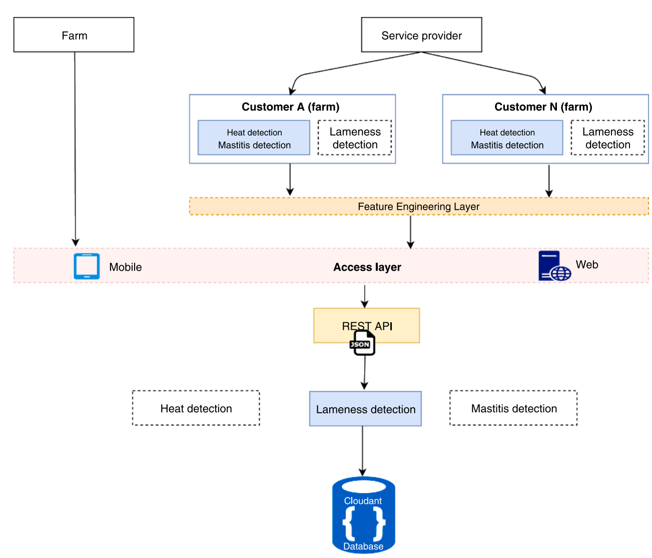


Fig. 5. Microservices based application flow for integration of services from different service providers.

It is important to note that this layer will be different for each service provider since the underlying sensor technology might be different. This in turn makes the developed system sensor agnostic. The output from the feature engineering layer is then passed to the access layer, which includes both mobile and web components. This then goes through a REST API which in turn calls the desired service.

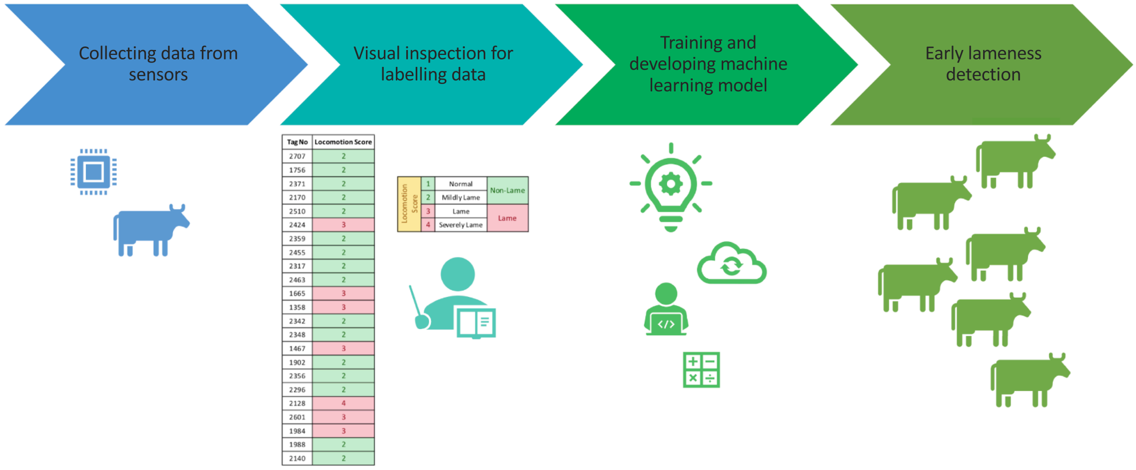


Fig. 6. A diagrammatic representation of the end-to-end pipeline of the developed solution illustrating: (1) data collection from sensors, (2) observation of animals by an animal expert to give locomotion score, (3) translating the human observer's expertise into a machine learning based system leading to early detection of lameness in cattle.

4. Materials, methods and machine learning model description

4.1. Data

The data from the sensors is sent via the receiver to the fog node, where it is pre-processed and aggregated into three behavioural activities—(1) Step count, (2) Lying time, and (3) Swaps. The choice of these 3 features is guided by literature study, which indicates that they are among the best predictors of a lame cow, or one transitioning to lameness (Thorup et al., 2015). The data is then summed to form daily time series. Out of 150 cows used in the trial, only 146 cows were used in the analysis. Only data from July to December 2017 was included in this analysis. During this period, 26 animals were reported as lame (cows were checked for lameness by either the agricultural science student or by the farmer). Because the number of lame animals was small, splitting the data into training and testing folds was made in a such a way that atleast 75% of the lame animals was put in the training fold and the rest in the testing fold. This was a challenge as the dataset was imbalanced, but because this was a live experiment, we hoped to re-train the models after sometime. The performance on both the training and testing are reported in a later section.

Fig. 6 gives a quick overview of the end-to-end pipeline of the developed solution illustrating: (1) data collection from sensors, (2) observation of the herd by an animal expert for locomotion scoring, (3) translating the human observer's expertise into a machine learning based system leading to early detection of lameness in dairy cattle. Table 2 presents the locomotion scoring scale system used by the agricultural science student during animal observation.

Table 2
Locomotion scoring scale system used by the agricultural science student while observing cows.

<table>
<tr><td rowspan="4">Locomotion Score</td><td>1</td><td>Normal</td><td rowspan="2">Non-Lame</td></tr>
<tr><td>2</td><td>Mildly Lame</td></tr>
<tr><td>3</td><td>Lame</td><td rowspan="2">Lame</td></tr>
<tr><td>4</td><td>Severely Lame</td></tr>
</table>

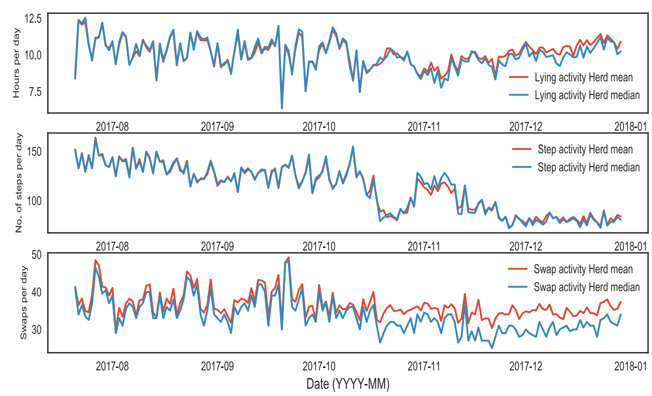


Fig. 7. Comparing the Mean and Median of the various Animal Activities.

4.2. Machine learning model and data analytics

4.2.1. Cow profiling

In order to build robust profiles that are distinguishable by the learning model, it is important to understand how each test profile (lame and non-lame) relates to the rest of the herd. The most common approach would be to compare the activity level of lame and non-lame

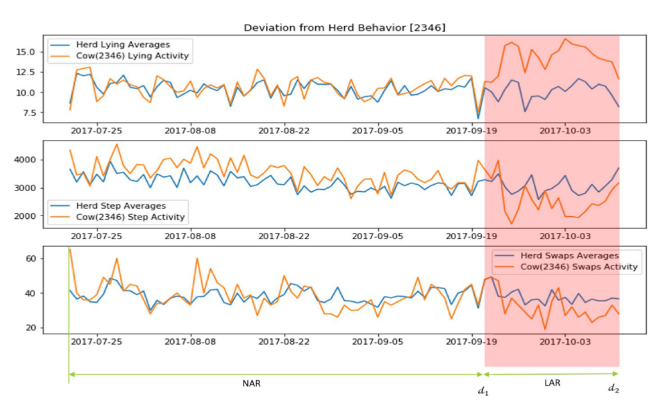


Fig. 8. Relationship between herd mean and cow activity for cow 2346.

animals and investigate how these deviate from the mean of the entire herd. However, the mean can be affected by a single value being too high or low compared to the rest of the sample. This is why a median is sometimes taken as a better measure. Fig. 7 compares the mean and median of the herd. The results show that these almost trace out each other for all the three activities; lying time, step count and swaps. This is one of the features of a normal distribution, and therefore it would not matter whether the mean or median is used. Thus, we decided to use herd mean in our analysis.

Authors in (Stephenson and Bailey, 2017) have argued that animals grazing within the same pasture can influence the movement, grazing locations, and activities of other animals randomly, with attraction, or with avoidance; therefore most of the animals will have their activity levels equal to the herd mean. For this reason and the one discussed above, the herd mean was used as the baseline and any deviation from such behaviour due to lameness will be classified as an anomaly. It is also important to note that this will eliminate the effects of external factors as these will be affecting the whole herd and only leave the individual effects of lameness on the cow.

We further define the Lame Activity Region (*LAR*) and the Normal Activity Region (*NAR*) as shown in Fig. 8. Once a cow is identified as lame, we compare the herd mean for all the activities to that cow's activities and define a region $d_1 \leqslant D > d_2$, where d_1 is the day the activity starts to deviate from the herd activity mean, d_2 is the day that cow is identified as lame. As lameness is a transition, we ascertain that the cow will remain lame after that until it's out of its lameness cycle. D is the entire duration between d_1 and the days after d_2 until the cow is out of its lameness cycle. It's the whole duration between d_1 to the last day when the cow was still lame. The values of d_1, d_2, and D will vary for each cow as some may have longer lameness cycles than others, and also depending on when the cow is identified as lame. This is motivated by the fact that lameness is a transition from normal behaviour to lameness and back, it will probably start before it is seen and even continue after treatment until the cow becomes normal again. Once we define the LAR, the rest of the graph is treated as the NAR.

Normal Profile,

To form the normal profile, we define a small window $\Delta\mathscr{W}_n$ within NAR for each of the normal cows and calculate mean absolute deviation N_{mad} for a given period of time.

$$N_{mad} = \frac{\sum_{j=\Delta\mathscr{W}_n}^{\mathscr{W}_n} |H_m - C_i|}{\mathscr{W}_n} \tag{1}$$

Here H_m is the herd mean, C_i is the cow activity and $\mathscr{W}_n$ is the window size of NAR.

Lame Profile

To form the lame profile, we define a small window $\Delta\mathscr{W}_l$ within LAR for each of the lame cows and calculate mean absolute deviation L_{mad} for a given period of time.

$$L_{mad} = \frac{\sum_{j=\Delta\mathscr{W}_l}^{\mathscr{W}_l} |H_m - C_i|}{\mathscr{W}_l} \tag{2}$$

Here H_m is the herd mean, C_i is the cow activity and $\mathscr{W}_l$ is the window size of LAR.

The process is repeated for all the lame and non-lame cows. The results of this are plotted in a density distribution plot as shown in Fig. 9.

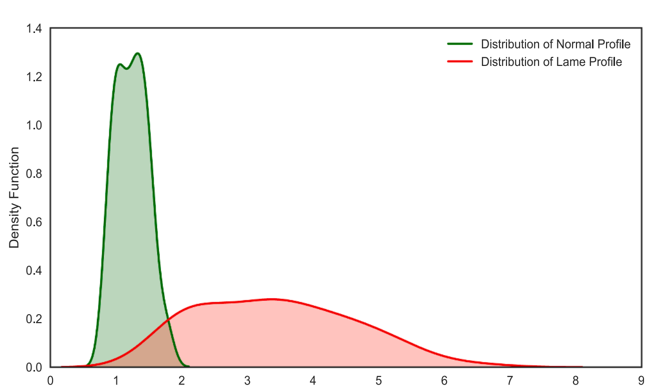


Fig. 9. Density distribution plot comparing the Normal and Lame profiles.

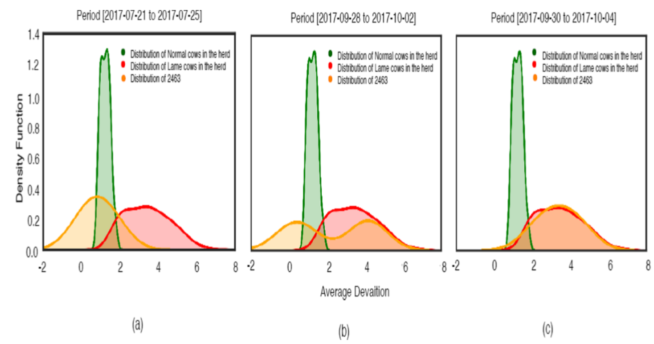


Fig. 10. Comparing the distribution of cow 2463 against the normal and lame profile at three different stages.

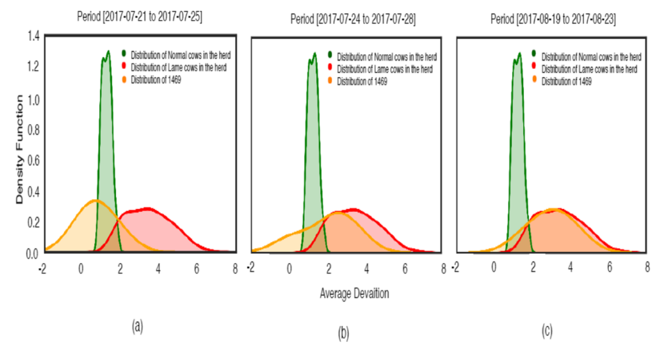


Fig. 11. Comparing the distribution of cow 1469 against the normal and lame profile at three different stages.

Relationship between individual cows, Normal (Non-Lame) and Lame profiles

To test the viability of the profiles, randomly chosen cows that have at least been identified as lame at some point during the experiment were used (these were not used to form the profiles above). The goal was to go back in time and see how these relate to the constructed profiles before they get lame, when they are lame and when they transition back to normal behaviour. Using Eq. (3), we define a window slice $\Delta\mathscr{W}_s$ (the optimal number of days were chosen after a repetitive process) starting at the beginning of the experiment when the cow is not lame. We then slide through time as we calculate the Average Deviation (AD) within each $\Delta\mathscr{W}_s$ for each of the cows, and for each of the activity.

$$AD = H_m - C_i \tag{3}$$

Here H_m is the herd mean within $\Delta\mathscr{W}_s$ and C_i is the cow activity. This is repeated as we slide the window. The results of this are plotted as density distribution and compared with Fig. 9.

The three graphs (a, b and c) for both Figs. 10 and 11 show periods of transition from normal to lameness for the two cows 2463 and 1469.

In Figs. 10(a) and 11(a), both animals are non-lame and the distributions relate to the Normal cows profile distribution. In Figs. 10(b) and 11(b) the distribution starts to shift to the right. Fig. 10(b) has two peaks. One relates more to the normal profile and the other to the lame profile. Fig. 11(b) on the other hand has one peak and this is mid way between both the normal and the lame profile. This kind of behaviour is justifiable because lameness is a transition. Perhaps this could be the best stage for the system to identify early lameness. Finally in Fig. 10(c) and 11(c), the distributions overlap with the lame profile distribution. It is important to note, even at this stage lameness is not yet visually detectable by the farmer for both cows.

4.2.2. Clustering

From the above, it was discovered that not all animals behaved the same way. For example, some animals had their activity levels (step count, lying time and swaps) tracing out the herd mean, others with activity levels always higher than the herd mean and, the other category always lower than the herd mean. It's also important to note that even when they became lame they had different activity levels depending on which category they belonged to. Therefore the clustering model is based on this observation. We set thresholds, and based on this we form three clusters.

To define a cluster, we define a window of size k days, and calculate MAD (Mean Absolute Deviation) between the cow activity and the herd mean for all the three activities.

$$C_{MAD} = \frac{\sum_{k=1}^{n} |H_m - C_i|}{k} \tag{4}$$

Here H_m is the herd mean within a defined window, C_i is the cow activity for activity i and k is the window size. We varied the values of k while testing the accuracy of the classification model and concluded that 14 days would be the optimal number of days to define a cluster. Based on MAD, we defined a threshold h. Now based on this threshold, and the following criterion, we define three clusters. If any two of the activity levels are below a certain threshold, then that animal is assigned into one of the below clusters:

Active

These are animals in the herd that have activity levels always higher than the herd mean. These have the mean deviation of any two of the activities is greater than threshold h.

Normal

These are animals in the herd that have activity levels always tracing out the herd mean. These have the mean deviation of any two of the activities is less than h but great or equal to zero.

Dormant

These are animals in the herd that have activity levels always lower than the herd mean. These have the mean deviation of any two of the activities less than zero.

The threshold was carefully chosen by a repetitive evaluation process, and was set to 1.7. The results presented in next section have been derived with h value equals to 1.7. It's also important to note that these clusters are dynamic, i.e., the animals keep changing the clusters they belong to. This can be caused by many factors like age and weather. So it is the role of the clustering model to keep regrouping the animals before selecting the appropriate classification model for that cluster (the best amount of time to re-cluster was found to be two weeks i.e., 14 days). Table 3 shows the distribution of the clusters as of writing of this article. The total number used to build clusters was 146 as three of the animals were eliminated due other health related issues and one animal lost the tag during the experiment.

Table 3
Distribution of the clusters.

Active	Normal	Dormant
25	109	12

4.2.3. Classification

Classification algorithms are a family of machine learning algorithms that output a discrete value. The output variables are sometimes called labels or categories. These kind of problems always require the examples be classified into two or more classes. Classification problems with two labels are called binary classification problems while those with more than two are called multi-class. We formulated our problem as a binary class problem with Lame being the positive class and Non-lame as the negative class. In general, to solve these kind of tasks, the learning model is usually tasked to produce a function $f: R^n \rightarrow \{1, ..., n\}$, where n is the number of labels. For example, let $\{X, Y\}$ denote the data set (feature, label), and θ the parameters, where:

$$X = \begin{bmatrix} x_{11} & x_{12} & x_{13} \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ x_{n1} & x_{n2} & x_{n3} \end{bmatrix} = \begin{bmatrix} Lying & Steps & Swaps \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ Lying_{n1} & Steps_{n2} & Swaps_{n3} \end{bmatrix}$$

$$Y = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} Lame \\ Non-Lame \end{bmatrix}$$

When $y = f(x)$, an input depicted by vector x will be assigned to a class label identified by y. It is important to note that there are other variants of functions f. For example f might output a probability distribution as opposed to a class label. At the time of writing, the feature matrix X was made up 3 columns. Each of the columns is a feature. These were chosen because most literature suggests that they more representative of an animal transitioning to lameness or one that is already lame. The vector Y consists of labels 0 and 1, where 0 indicates non-lame and 1 otherwise. Fig. 12 shows the overall work flow and data flow of training and testing of the designed model.

5. Results, evaluation and discussion

A brief demo-video of the developed system is available at Taneja et al. (2018a). Our initial work on age-based clustering of cows combined with data analytics to detect anomalies in their behaviour, and microservices based application design for integration of different services has been presented in Taneja et al., 2019a; Byabazaire et al., 2019; Taneja et al., 2018b respectively.

5.1. Rationale behind clustering

In a study about association patterns of visually observed cattle, Stephenson et al. (2016) concluded that herds with 40 or less cows did not exhibit preferential or avoidance associations. This means that they lived together as a single group. In contrast, larger herd sizes (53–240 cows) tended to form associations with other cows stronger than what you would expect by chance. Therefore, the clustering step is only relevant to large herd sizes. Needless to mention, automated lameness solutions are meant for large herd sizes as it is assumed that for small ones, the farmer can visually inspect and keep track of the cows' welfare easily. We compared the results of a one-size-fits-all model and a cluster specific models. Overall, cluster specific models reduced the classification error by 8% as compared to a one-size-fits-all model without clustering. For example, Fig. 13 shows an animal that was confirmed as lame from 03/12/2017 to 15/12/2017. The activity clustering based normal cluster model could correctly identify all the days the animal was lame, which has been illustrated in Fig. 13 using the highlighted red box. However, the one-size-fits-all model could only pick up some days as shown by the red points within the highlighted red box in Fig. 13.

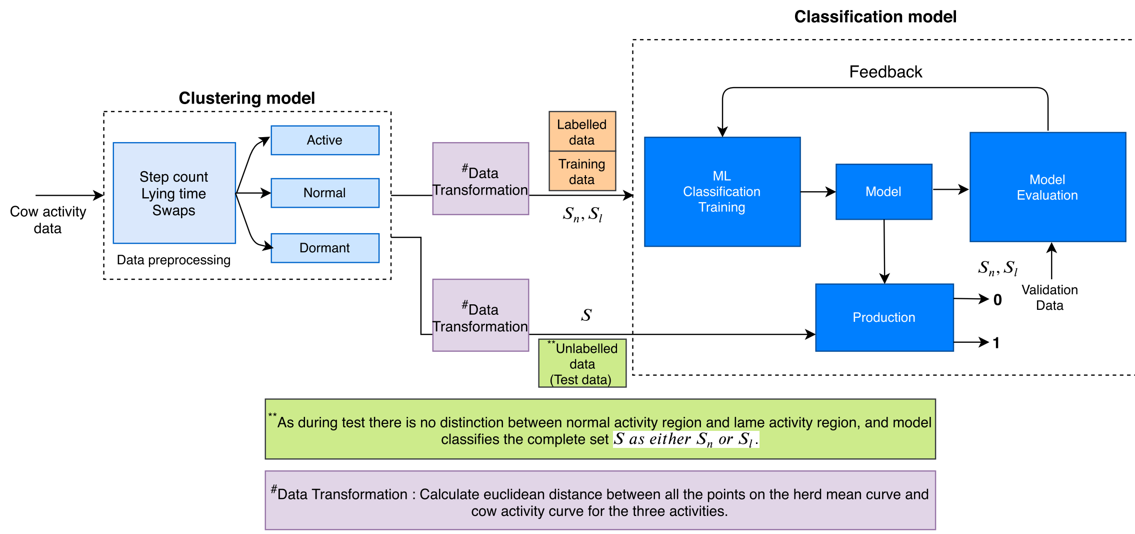


Fig. 12. Designed hybrid machine learning model and work flow illustrating the steps in process of data collection, clustering, transformation, classification, training, evaluation and production mode.

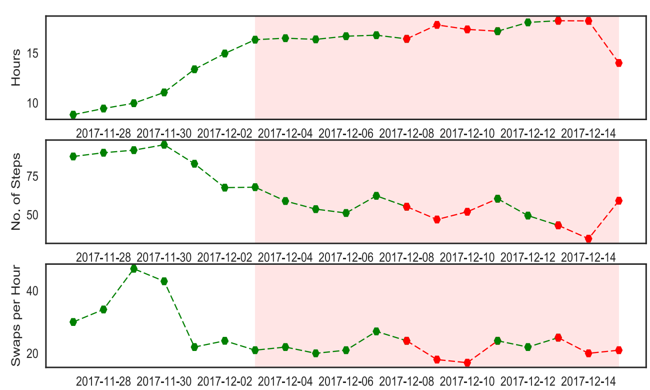


Fig. 13. Animal confirmed as lame between 03/12/2017 and 15/12/2017 but could not be correctly identified by a one-size-fits-all model. The highlighted red box shows that using activity clustering based normal cluster in the designed machine learning model, the system was able to detect animal as lame on 03/12/2017 i.e., starting of the highlighted red box; whereas the one-size-fits-all system was able to pick only some days, shown as red points in the figure. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 4
Lameness detection accuracy of the developed system.

Classification Model	Accuracy (in %)	Number of days before the visual signs of lameness appears
Random Forest	91	1
K-Nearest Neighbors (K-NN)	87	3

Table 5
Different K-values, accuracy of the developed system and early detection window size.

K-value	Accuracy (in %)	Number of days before the visual signs of lameness appear
2	91	1
3	89	2
4	**87**	**3**
5	81	1

5.2. Early lameness detection assessment

The problem was formulated as a binary classification problem with Lame as being the positive class and Non-lame as the negative class. These are denoted as (S_n) for the negative class and (S_l) for the positive class in the model diagram presented in Fig. 12. The training process reported in this study is unique from the previous approaches because it has a feedback loop added. After model validation, an agricultural expert or farmer re-annotates training data to improve the model accuracy.

Please note that once the activity based clustering (Section 4.2.2) is done, and LAR and NAR have been defined (cow profiling – Section 4.2.1), we then calculate the euclidean distance between all the points on the herd-mean curve and cow activity curve within each of these regions. This gives us two sets S_n and S_l, where S_n are the values from NAR and S_l are the values from LAR, and these form the two classes that are used in machine learning element of the developed system. These two sets (S_n and S_l) are fed into a K-NN machine learning classification model.

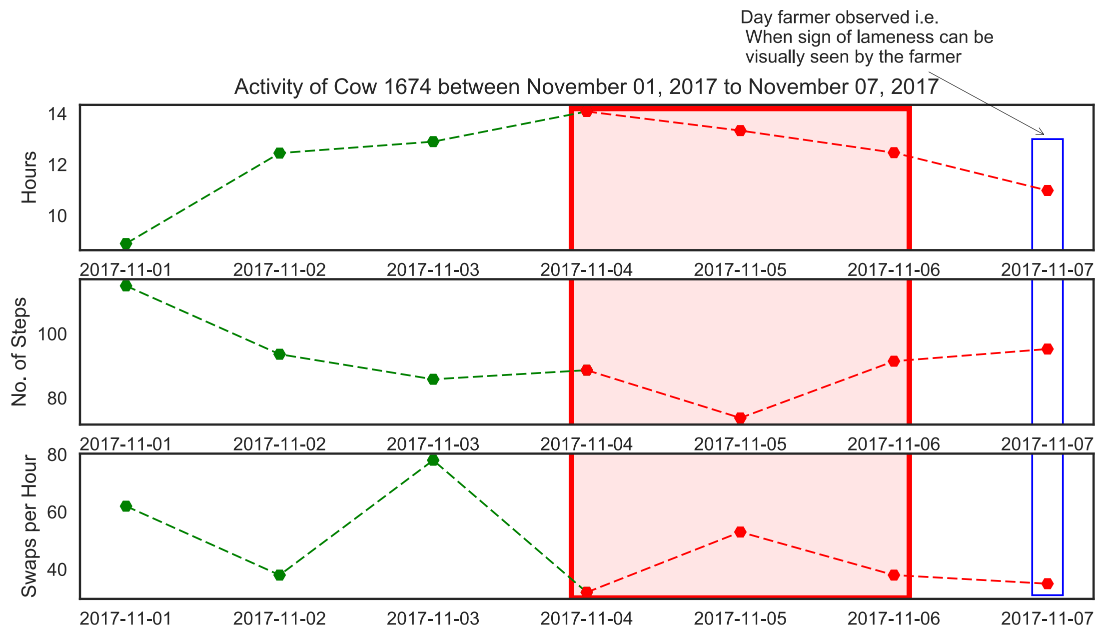
We experimented on a number of sklearn (Pedregosa et al., 2011) classification algorithms ranging from Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbors (K-NN) and Decision Trees. We selected K-NN classification algorithm, as it was best balanced in terms of accuracy and early lameness detection window as shown in Tables 4 and 5.

It is also important to note that although a different model was trained and built for each of the three clusters (i.e., three classification models – one for each cluster), results reported (performance and accuracy) in this study are only for the normal cluster. This is because it was not possible to efficiently evaluate the other two clusters as testing data in these was very small (i.e., imbalanced for a proper evaluation).

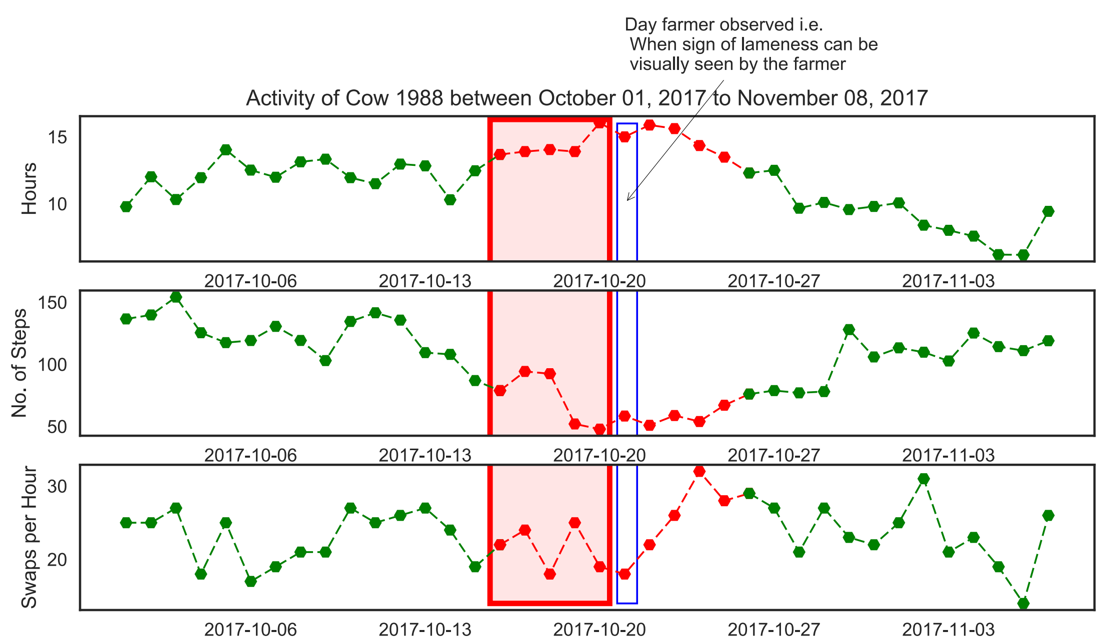
K-NN

This has a number of parameters that should be fine-tuned in order to achieve the desired results. Among these, we evaluated different K-values (2–5), which is the number of neighbours to consider while assigning the nearest class. We set the distance metric to minkowski. The highest accuracy was obtained with $k = 2$ although this was over fitting the data. Table 5 presents the accuracy of detection with different K-values, and also the length of the early detection window.

Optimal results were obtained at $k = 4$ which gave an accuracy of 87% with 3 days before the visual signs could be seen. In all, the normal cluster model had a sensitivity of 89.7% and specificity of 72.5%.



(a) The highlighted red box shows the number of days the cow was lame but undetected and to only be visually seen on 07/11/2017 (highlighted and arrowed blue-box), and the beginning of red dots and dotted line shows that model detected it three days before on 04/11/2017.



(b) The highlighted red box shows the number of days the cow was lame but undetected and to only be visually seen on 20/10/2017 (highlighted and arrowed blue-box), and the beginning of red dots and dotted line shows that model detected it three days before on 17/10/2017.

Fig. 14. Early detection of lameness by the developed model and late observation by farmer.

Fig. 15 shows some of the correct detections. One particular cow was confirmed as lame between 16/10/2017 and 25/10/2017 and the model could correctly classify all the days as shown by the red points in Fig. 15.

Fig. 14 shows two cases where the model was able to detect a cow being lame 3 days before its visual clues were available to the farmer. The highlighted blue box shows the day when it was visually detected by the farmer or animal expert, and the start of the red points shows when the model detected the cow to be lame, and highlighted box shows the number of days for which the visual sign didn't appear to be seen by the farmer or animal expert.

5.3. Reduction in data transfer: fog-cloud data reduction

Among the downsides of the existing approaches is that they are either fully cloud-centric in nature, i.e., all the data is sent to the cloud

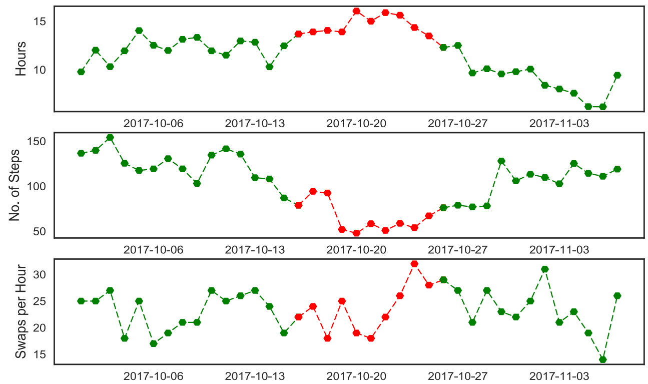


Fig. 15. Red points indicating lameness anomalies identified by the normal cluster model for cow ID 1988. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

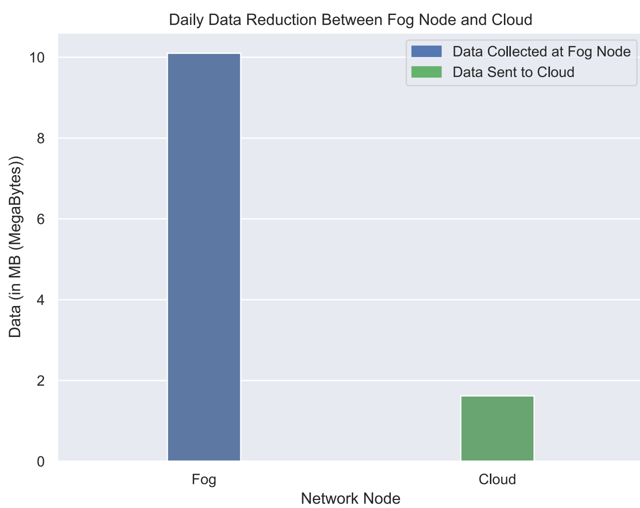


Fig. 16. Daily reduction in the amount of data between the fog node and the cloud.

for processing and analysis; or have just farm premises based system which limits the accuracy and intelligence (Rutten et al., 2013) of such systems as there are no dynamic and frequent updates.

In this work, we focused on the reduction of data exchanged between fog node and the cloud. We leveraged and utilized fog architecture in our work and were able to reduce data exchange between fog and cloud node from 10.1 MB to 1.61 MB on daily basis. Fig. 16 shows an 84% reduction in the amount of data that would otherwise have streamed to the cloud throughout the day. This aspect of data reduction becomes even more crucial while scaling up the farm and the herd, as the amount of data collected and streamed would then rapidly increase.

6. Conclusion

Our results suggest that building custom models for small groups of animals in the herd that share similar features within the herd improves the accuracy of the lameness detection as opposed to a one-size fits all approach. This approach becomes more important and practically viable with increase in size of the herd. Insights from our real world deployment suggest that activity based cluster specific models reduce the classification error of lameness detection by 8% as opposed to a one-size-fits-all approach. Using these clusters to then identify the anomalies in animal behaviour gives a better early detection. In our case, feeding the resultant cluster in K-NN (K-Nearest Neighbours) based classification models gives an accuracy of 87% with an early detection of 3 days window before any visual or clinical sign of lameness appears. It is because of this carefully blended design of clustering and classification model that results in a hybrid model for early lameness detection in dairy cattle.

Further, the fog-based computational assistance enables the intelligent processing of data closer to the source, thereby leading to an 84% reduction in the amount of data transfer to cloud. Another key lesson learned is that any of the edge/fog/cloud resources of the overall architecture if considered in isolation would not be able to manage the developed IoT application, without compromising on functionalities or performance. And thus a careful coordination of edge, fog and cloud components is required as presented in this work.

7. Ongoing and future work

To further validate the proposed approach for early lameness detection, we are expanding the work undertaken to date through the execution of a use case in the IoF2020 project[3] named MELD[4]. The MELD project is building and expanding upon this existing work, and integrating it into the IoF2020 dairy farming technology trials with deployments in Portugal, Israel and South Africa. It aims to leverage sensor technologies from two different vendors on a combined total of approximately 1000 cattle, consisting of both beef and dairy.[5]

In future work we also intend to investigate a more robust clustering technique as the current one is only based on threshold. Also, we plan to evaluate the other cluster models. Further, in context of efficient in-network resource utilization and increasing system resilience, one of the possible directions of future work is to look into distributed learning (Konecný et al.) and distributed data analytics (Taneja et al., 2019c; Chang et al., 2017) based approaches in such real-world IoT based deployments.

Once the developed technology has been validated on a number of farms with different geographical and environmental settings, the goal is to roll out the technology to the vendors' customer base as an added feature through licensing.

CRediT authorship contribution statement

Mohit Taneja: Investigation, Software, Methodology, Data curation, Writing - original draft, Formal analysis, Validation. **John Byabazaire:** Investigation, Software, Methodology, Data curation, Formal analysis, Validation. **Nikita Jalodia:** Methodology, Writing - review & editing, Visualization. **Alan Davy:** Supervision, Funding acquisition, Conceptualization. **Cristian Olariu:** Resources, Formal analysis, Supervision. **Paul Malone:** Writing - review & editing, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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[3] Internet of Food & Farm 2020, https://www.iof2020.eu/https://www.iof2020.eu/.

[4] MELD stands for **M**achine Learning based **E**arly **L**ameness **D**etection in Beef and Dairy Cattle.

[5] The collected data from the existing real-world deployment is available to be shared with the academic research community upon request.

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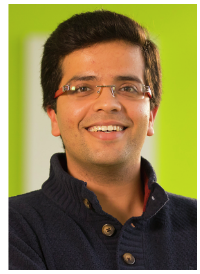
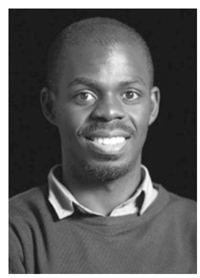


Mohit Taneja is currently working as a software research engineer, and also as a PhD researcher with Emerging Networks Laboratory at Telecommunications Software and Systems Group of Waterford Institute of Technology, Ireland. He joined them in 2015 as a Masters Student as a part of the Science Foundation Ireland (SFI) funded CONNECT Research Centre. He was a part of the SFI-CONNECT-IBM project termed SmartHerd, which has now been extended with follow-on IoF2020 project termed MELD, which is a project to detect early stage lameness in cattle with the help of technology. His research focuses on fog computing support for Internet of Things applications. His current research interests include Fog and Cloud Computing, Internet of Things (IoT), Distributed Systems, and Distributed Data Analytics. He received his Bachelor's Degree in Computer Science and Engineering from The LNM Institute of Information Technology, Jaipur, India in 2015.



John Byabazaire is currently a PhD student in school of computer science, University College Dublin working on IoT systems for data collection in precision agriculture. Before that, John pursed a MSc in Computer Science from Waterford Institute of Technology and due to graduate. He received his BSc in Computer Science from Gulu University in 2013. Alongside his current PhD study, John continues to research e-learning for low bandwidth environments, Software Defined Networking, Network Function Virtualization, and Remote Sensing, IoT (Internet of Things) and Fog Analytics.

Nikita Jalodia is a PhD Researcher in the Department of Computing and Mathematics at the Emerging Networks Lab Research Unit in Telecommunications Software and Systems Group, Waterford Institute of Technology, Ireland. She is working as a part of the Science Foundation Ireland funded CONNECT Research Centre for Future Networks and Communications, and her research is based in Deep Learning and Neural Networks, NFV, Fog Computing and IoT. She received her Bachelor's Degree in Computer Science and Engineering from The LNM Institute of Information Technology, Jaipur, India in 2017, with an additional diploma specialization in Big Data and Analytics with IBM.

Alan Davy received the B.Sc. (with Hons.) degree in applied computing and the Ph.D. degree from the Waterford Institute of Technology, Waterford, Ireland, in 2002 and 2008, respectively. Since 2002, he has been with the Telecommunications Software and Systems Group, originally as a student and then, since 2008, as a Post-Doctoral Researcher. In 2010, he was with IIT Madras, India, as an Assistant Professor, lecturing in network management systems. He was a recipient of the Marie Curie International Mobility Fellowship in 2010, which brought him to work at the Universitat Politecnica de Catalunya for two years. He is currently Head of Department of Computing and Mathematics in School of Science and Computing at Waterford Institute of Technology (WIT), Waterford, Ireland. Previously, he was Research Unit Manager of the Emerging Networks Laboratory with the Telecommunications Software Systems Group of WIT. He is coordinator of a number of national and EU projects such as TERAPOD. His current research interests include Virtualised Telecom Networks, Fog and Cloud Computing, Molecular Communications and TeraHertz Communication.

Cristian Olariu received his B.Eng. degree in 2008 from the Faculty of Electronics and Telecommunications, Politehnica University of Timisoara, Romania, and his Ph.D. degree in 2013 WIT in VoIP over wireless and cellular networks. He was a research engineer with the Innovation Exchange, IBM Ireland, and is currently a research scientist with the Huawei Research Centre, Ireland. His interests are in computer networks optimisation, applied predictive modelling, anomaly detection, root cause analysis, deep neural nets, machine learning and AI.

Paul Malone graduated from Waterford Institute of Technology with a 1st class honours degree in 1998 and completed a research MSc in 2001. Paul has worked on researching technologies and techniques related to IT security in the areas of distributed trust and reputation management and privacy and data protection controls. Paul is currently coordinating an Agri-Tech use case sub-project of the H2020 IoF2020.eu project applying machine learning technologies in detecting early stage lameness in cattle.