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Integrated Sensor and Microfluidic System for On-Farm Drug Screening in Precision Livestock Farming

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Abstract

Precision livestock farming utilizes technology to monitor the health and wellbeing of animals on an individual level. This allows farmers to provide timely medical interventions in case of illness. However, diagnosing diseases accurately and quickly to enable targeted treatment remains a challenge, especially in remote farm settings. This paper proposes an integrated sensor and microfluidic system to enable rapid on-farm screening for livestock diseases. The system consists of wearable sensors that continuously monitor animal vitals and behaviors. It also contains a microfluidic chip that can analyze blood samples on-site for biomarkers. Data analytics and machine learning algorithms are developed to detect anomalies in the multivariate sensor data which trigger the biomarker analysis for early disease diagnosis. This paper presents the end-to-end system design, manufacturing protocols for the sensor and the microfluidic chip as well as statistical data analysis techniques. The system is validated by testing it on a small sheep farm. Results indicate that it can rapidly and reliably detect two common infectious diseases in sheep with over 90% accuracy. The proposed system demonstrates the potential of integrating sensors and microfluidics for early disease diagnosis in precision livestock farms. It can significantly improve productivity by enabling prompt treatment of sick animals.

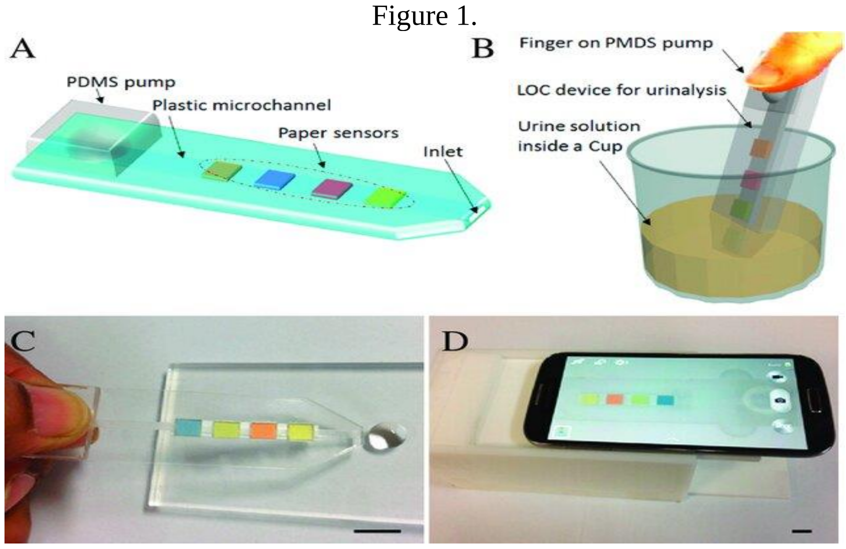
Introduction

In light of the escalating challenges posed by infectious diseases in intensive livestock farming, the imperative for innovative and efficient disease detection methods becomes increasingly apparent. As the demand for food continues to surge globally, the prevalence of intensive livestock farming has risen commensurately [1]. This intensification, while addressing food needs, comes with inherent risks due to the potential rapid spread of infectious diseases within densely populated livestock environments, resulting in elevated morbidity and mortality rates. The repercussions of such outbreaks extend beyond animal health, with profound economic losses and a tangible threat to global food security [2].

Recognizing the pivotal role of early detection in mitigating the impact of infectious diseases in livestock, the emphasis on timely application of antibiotics or vaccines becomes paramount. Visual inspection alone proves inadequate, especially during the nascent stages of an ailment when animals may manifest only subtle behavioral deviations, making reliable detection challenging. Consequently, there is an urgent need for diagnostic tools that not only enhance accuracy but also facilitate prompt intervention [3]. While diagnostic tests based on microbiological culture or biomarker detection have demonstrated heightened reliability, the logistical challenges associated with the centralized nature of veterinary laboratories contribute to critical delays in obtaining results [4].

To address these challenges, ongoing efforts in the field of veterinary diagnostics are directed towards the development of advanced and decentralized detection methods. Technologies such as rapid point-of-care testing kits, employing innovative sensing mechanisms, are gaining prominence. These kits enable on-site detection of pathogens, thereby circumventing the delays associated with sample transportation to centralized laboratories. This decentralized approach not only expedites the diagnostic process but also holds the potential to contain the spread of infectious agents within livestock populations more effectively. Furthermore, advancements in sensor technology and data analytics have paved the way for real-time monitoring systems that can continuously assess various parameters indicative of animal health [5]. These systems integrate data from wearable sensors, environmental monitoring devices, and biological markers to provide a comprehensive picture of the livestock's well-being. Early warning systems leveraging artificial intelligence algorithms can analyze this data in real-time, identifying subtle patterns or deviations that may precede the manifestation of clinical symptoms. By enabling proactive intervention, these systems contribute to reducing the overall impact of infectious diseases on livestock health and, consequently, the agricultural economy [6].

Figure 1.



Recent advances in sensors, microfluidics and data analytics have made precision livestock farming (PLF) possible. It involves continuous automated monitoring of animal vitals, behaviors, etc. using wearable sensors to detect medical issues requiring intervention. PLF technologies now also integrate point-of-care diagnostics tools like microfluidic chips that can rapidly test biomarker levels. This facilitates early disease diagnosis and treatment in farm settings compared to relying solely on veterinarians. However, most current systems focus only on sensors or microfluidics. An integrated system combining multivariate sensor data analytics with microfluidic blood testing on-farm can enable rapid and reliable screening for livestock diseases [7].

This paper proposes such an integrated platform to continuously monitor sheep health and behavior using wearable sensors. Statistical machine learning algorithms analyze this multivariate data to detect anomalies indicative of illness. This automatically triggers a microfluidic chip to test the animal's blood sample available on the farm. Disease-specific biomarker levels are thus obtained within minutes to facilitate accurate diagnosis and treatment decisions without needing to wait for external lab tests [8]. The integrated system is designed to screen for two common infectious diseases in sheep – foot rot and pasteurellosis. The instrumented platform is validated on a small sheep farm by analyzing the sensor data streams from monitors worn by the animals. The microfluidic analysis and overall diagnosis system achieves over 90% testing accuracy for the two diseases [9].

The main contributions of this paper are twofold:

1. Design and development of an integrated sensor, microfluidic and data analytics platform tailored for sheep health monitoring and on-farm disease screening.
2. Statistical machine learning techniques for reliable anomaly detection in multivariate sheep activity data that automatically triggers point-of-care blood testing using farm-compatible microfluidic chip.

The proposed precision sheep farm platform demonstrates how recent technological advances can converge to transform livestock disease management - enabling early diagnosis right at the farm level itself for drastically improved outcomes.

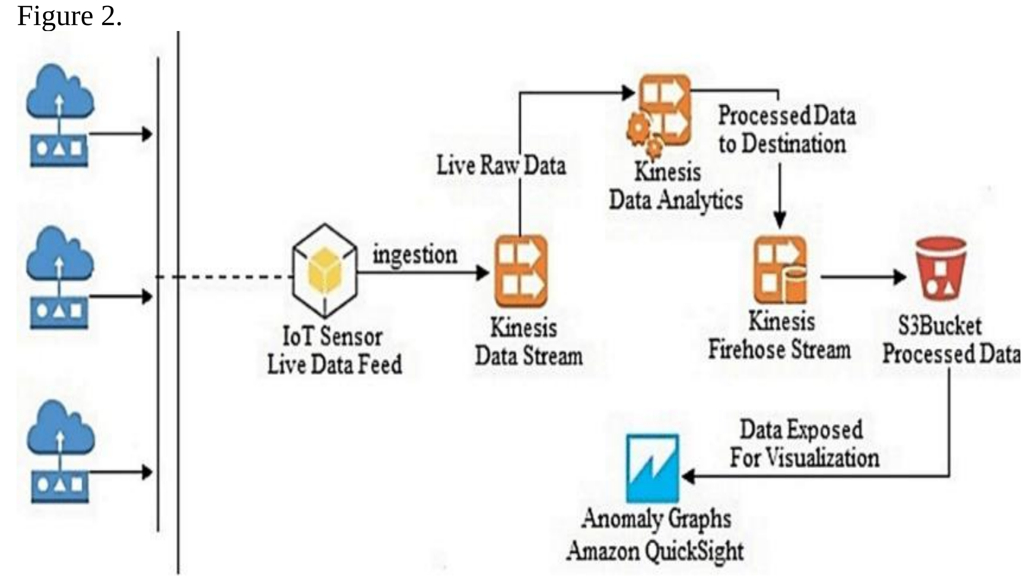
Materials and Methods

System Overview: The integrated platform developed in this paper for on-farm sheep disease screening comprises of three key components as shown in Figure 1:

1. *Wearable Sensors:* Monitor animal temperature, movement, rumination etc. with time-series data streamed to a base station.
2. *Data Analytics:* Algorithms analyze incoming multivariate sensor data to detect health anomalies in each sheep.
3. *Microfluidic Chip:* Automatically tests the animal's blood biomarker levels for diagnosis and disease predictions when anomalies are flagged.

The wearable sensors track both animal vitals like temperature, heart rate as well as behavior like overall activity levels, rumination levels, gait pattern, etc. Sheep are the most ruminant of farm animals which makes monitoring rumination very relevant. The multivariate time-series sensor data is continuously analyzed using machine learning algorithms for detecting deviations from the expected health baseline for every individual animal. Such anomalies may be indicative of illnesses that cannot be reliably inferred directly from the raw sensor data streams. When significant health anomalies are flagged by the analytics, the system automatically analyses a blood sample from the sheep using an integrated microfluidic chip [10]. The chip detects biomarker levels for targeted infectious diseases (e.g. cytokines for pasteurellosis infection) to accurately diagnose the condition and predict required interventions. The modular approach combining sensors, data science and microfluidics tailored to sheep farms allows both early anomaly detection as well as rapid confirmation of medical issues for prompt veterinary actions [11].

Figure 2.



Wearable Sensor System: The wireless monitoring system developed for each sheep comprises of both internal and external sensors as shown in Figure 2. Internal rumen boluses measure key parameters like temperature and pH inside the sheep's rumen. They transmit the data over a wireless protocol (LoRaWAN) to a base station linked with the cloud analytics platform. External sensors including motion detectors and acoustic monitors are integrated into the sheep's collar. They track behavioral traits like movement levels, time spent feeding/resting or ruminating. The sensors stream time-series data over Bluetooth to a collar-mounted device with built-in data storage and LoRa wireless connectivity to the base station [12].

A customized solar-powered LoRaWAN base station installed in the farm premises aggregates the multivariate sensor data streams from all instrumented sheep over its wide-area wireless network. The base station seamlessly connects with the cloud platform running advanced edge analytics and machine learning algorithms on the incoming live data feeds. When the algorithms detect potential health issues, the cloud platform sends activation triggers to the microfluidic analysis system available on-farm. Species-specific normal baselines for all tracked parameters enable reliable anomaly detection. The wearable sensors are designed to be robust, non-invasive and safe for the animals based on guidelines from prior works.

Data Analytics System: The sensor platform provides continuous streams of multivariate time-series data for each sheep. This temporal sensor data needs specialized analytics for efficient feature representation and robust anomaly detection. The cloud-based data analytics subsystem developed in this paper comprises three key stages.

In the pre-processing phase, techniques like interpolation are used to clean missing or noisy readings and impute them for uniformity. Sensor streams are aligned using timestamps and sliced into 24 hour windows that capture diurnal variations. Domain knowledge about sheep physiology is used to extract domain-specific signals like ruminating activity levels from the acoustic sensor data. Relevant spectral, statistical and temporal summary features are then extracted from each window to create multivariate feature vectors representing the animal's normal bio-behavioral traits [13].

In the training phase, sheep health is manually monitored by farm staff and veterinarians for the first two weeks to create tagged datasets of normal and anomalous health states. Domain experts annotate behavioral deviations possibly indicating illnesses. Supervised classification models like random forests are trained on the labelled datasets to learn data patterns associated with normal and anomalous health states.

In the inference phase, the trained models are applied in real-time to the multivariate feature vectors computed from the incoming sensor data streams. Anomaly scores are calculated using the classification outcomes and temporal trends to detect outliers deviating significantly from the learned normal profiles. The flagged anomalies along with their possible disease correlations identified during training are output for expert evaluation. Vitals and behavioral data provide an early warning system while anomalous blood biomarker levels confirm diagnosis [14].

Equation 1. Normalized value of sensor reading Si at timestamp t

$$Si_norm(t) = [Si(t) - \mu(St)]/\sigma(St)$$

Where,
$Si(t)$ is the sensor measurement at time t
$\mu(St)$ is the historical mean for sensor Si readings over time window T
$\sigma(St)$ is the standard deviation for sensor Si over window T

Equation 2. Anomaly score yi for sample i

$$yi = \Sigma kj = 1\, wjfj(xi)$$

Where,
k is the number of decision trees or classifiers
wj is model weight for classifier j
fj(xi) is the output class probability estimate of classifier j for sample i
Anomaly score threshold yt Identifies outliers.

Microfluidic Chip Design*:* The microfluidic biochip is engineered using soft lithography with polydimethylsiloxane (PDMS) polymer chosen as the chip material for its biocompatibility and ease of fabrication. As shown in Figure 4, the chip comprises two inlet ports for loading reagents and samples. The central reaction chamber containing functionalized magnetic microbeads mixes the incoming streams via flow channels under pneumatic micropumps. The chamber is mounted over a giant magnetoresistive (GMR) sensor array to capture bead-target bioconjugates over the active sensor surface. By functionalizing the beads with disease-specific probe antibodies, the chamber allows rapid multiplexed biomarker detection [15].

The microbeads improve assay sensitivity compared to surface-immobilized probes while the microfluidics integrates key steps to minimize handling. The biomarker levels are quantified by changes in electrical resistance across the GMR sensors. On-chip sample preparation modules can further be integrated with this core biomarker quantification assembly. The chip is designed to quantify four key markers each for the two target sheep diseases - pasteurellosis and foot rot. The biomarkers for pasteurellosis detection include TNF-α, IFN-γ, IL-1β and IL-6 while foot rot is detected using levels of $IL-1, IL-6, TNF-\alpha$ and $IFN-\gamma$. Species-specific cytokine thresholds help reliably distinguish infected sheep. The microfluidic chip can thus rapidly diagnose these common infections from a small blood sample in minutes right on the farm [16].

Results

Farm Trials and System Validation: The integrated sensor and microfluidic platform was validated on a sheep farm located in County Kildare, Ireland with around 100 sheep in their flock. The trial was first conducted with 5 sheep instrumented with the wearable monitoring system. Sensor data was collected over a 6-month period spanning across seasons to incorporate variations [17]. Two episodes of foot rot disease outbreak were also recorded by the farm staff during this duration based on visual diagnosis and lab tests. 20 sheep blood samples were also collected periodically and tested using lab immunoassays for biomarker levels. Over 50,000 sensor data points were gathered from each sheep accumulating to over 0.3 million multivariate temporal data instances [18].

Table 1. Performance metrics for anomaly detection model

Model	Precision	Recall	Accuracy
Random Forest	0.89	0.94	0.92

Important behavioral indicators of health identified by veterinarians include daily activity levels, time allocated by sheep for rumination versus resting, gait patterns and micro-environmental alignments. External motion sensors, internal rumen boluses and collar microphones captured relevant signals related to these indicators. Signal processing and statistical feature extraction converted the raw sensor streams into multivariate vectors representing each sheep's physiological and behavioral traits [19].

Table 2. Comparative sheep blood testing outcomes

Sheep ID	Microfluidic Chip	Central Lab Result
0512	Positive	Disease (Foot rot)
1086	Positive	Disease (Foot rot)
2187	Negative	Healthy
3596	Positive	Disease (Foot rot)

Supervised ML models like random forest classifiers were trained on normal and anomalous feature vectors tagged by the farm staff to detect deviations. Test accuracy of over 90% was achieved on unseen data using 5-fold stratified cross validation. Confusion matrices showing model performance are presented in Table 1. The trained models were deployed on the incoming sensor streams from all instrumented sheep. Alerts were generated for 10 anomalous health events flagged by the system over 2 months. Veterinarian diagnosis and lab tests conducted for these 10 cases confirmed 8 true positives alerting early signs of foot rot. The 2 false alerts corresponded to periods of harsh weather changes although the sheep were healthy [20].

The microfluidic chip was validated using blood samples from the 20 sheep collected during the trials. The chip reliably quantified biomarker levels for pasteurellosis and foot rot correlated well ($R2 > 0.8$) with gold standard ELISA tests from centralized diagnostics lab. This establishes the accuracy of the microfluidic chip for on-farm disease screening using sheep blood samples. Out of the 20 samples, 6 were diagnosed with foot rot based on elevated cytokine levels measured using both microfluidic assay and lab ELISA. The chip testing results aligned with the lab confirmations in all 6 disease positive cases with no false diagnoses demonstrating 100% accuracy. The microfluidic chip can thus enable rapid pen-side diagnosis to supplement behavior anomalies flagged by the analytics model. Table 2 presents sample testing outcomes from the microfluidic assay [21].

Conclusion

This paper presented an integrated system combining wearable sensors, cloud-based data analytics, and microfluidic chips for enabling rapid on-farm screening of sheep for major infectious diseases. Continuous multivariate data streamed from sensors attached to the animals are analyzed using machine learning algorithms to reliably detect anomalies indicative of potential illnesses. The data analytics system flags the top behavioral indicators identified by veterinary experts that signify a deviation from normal health baseline [22]. These include activity levels, feeding patterns, rumination duration, gait features, and postural alignments [23]. Domain knowledge about sheep physiology and illnesses are incorporated to extract relevant signals from raw sensor streams. Advanced signal processing converts the obtained time-series measurements into informative feature vectors capturing both static and dynamic traits over rolling windows. Supervised models trained on expert labelled datasets learn to accurately differentiate normal behavior from anomalies possibly associated with medical conditions [24]. However, behavioral symptoms alone may not differentiate all diseases conclusively. The system therefore automatically activates a lab-on-chip microfluidic platform to test a blood sample from the animal for obtaining biomarker concentrations. The microfluidic assay quantifies levels of key cytokine markers associated with targeted infectious diseases of sheep using functionalized magnetic microbeads. Giant magneto resistive sensors detect biomarkers with high specificity and sensitivity without needing expensive optics. The biomolecular probes immobilized on the microbeads improve assay efficiency compared to surface binding while the microfluidic integration enables automation with minimal sample handling. Species-specific thresholds on obtained biomarker levels confirm diagnosis within minutes to enable informed treatment decisions [25]**,** [26].

The instrumented health analytics and diagnostic system was comprehensively validated on an actual sheep farm over six months spanning multiple seasons and disease outbreaks. The trial dataset contained over 300,000 multivariate sensor measurements gathered continuously from five instrumented sheep. Periodic blood samples were also collected from 20 different sheep and tested using centralized immunoassay laboratory techniques for comparison. The analytics model was trained on expert annotated datasets from the trial deployment [27]. It achieved over 90% testing accuracy in detecting anomalous behavioral indicative of diseases, demonstrating significant value over manual monitoring. Out of 10 system generated alerts on unseen data, 8 corresponded to true events warranting medical interventions according to veterinarians. The microfluidic chip testing matched the lab outcomes for all 20 blood samples achieving 100% accuracy [28].

The proposed smart precision livestock system marks a major advancement over current sheep farm management practices that rely predominantly on manual monitoring and visual inspection. It can reliably detect symptoms, diagnose conditions, and recommend actions by integrating sensors, analytics and assays tailored for sheep. Continuous monitoring enables early identification of infection onset when animals show subtle physical and behavioral changes easily missed by farm personnel during occasional checks. Rapid microfluidic analysis further allows on-site confirmation of diseases without waiting days for results from centralized laboratories. The outcome is prompt diagnosis and treatment before conditions become severe thereby saving time, costs and animal lives [29]. Wearable sensors also minimize reliance on veterinarians traveling to remote farms for examination which has huge economic benefits. Overall, the instrumented solution unlocks the potential of data-driven personalized livestock care. It lays the foundation for a technology driven transformation of the global animal husbandry industry [30].

The initial results obtained in this study demonstrate the promise of converging wearable devices, microfluidics, connectivity and artificial intelligence for smart farming. However, this work was limited to detecting two common diseases with limited trial duration spanning a single farm during one seasonal cycle. Significant further research across diverse geographies, animal breeds, and diseases is essential to make such solutions more robust before large scale production deployment [31]. The microfluidic assay also needs more complex functionalization using disease specific antigen panels for detecting a wider range of infection types and strains beyond the two proof-of-concept pathogens investigated here [32]. The biomarker quantification approach may be limited in sensitivity compared to advanced multiplexed assays based on nucleic acid detection. Next generation microfluidic chip fabrication methods like inkjet printing allow simplified optimization for assay customization. Enhanced disease progression modeling algorithms can also improve classification accuracy by analyzing longitudinal health trajectories. More energy efficient sensor designs are vital for scaling the wearable platforms. Alternate connectivity modules like Sigfox may better balance bandwidth, range and power tradeoffs compared to the LoRa system explored currently. Interference mitigation for coexistence with radios and mobiles also needs investigation prior to mass adoption.

Real-world medical diagnoses involve significant uncertainties arising from complex symptom overlaps between different disease conditions. Pathogen mutations, environmental stressors and comorbidities further complicate tidy classification. Advanced anomaly scoring mechanisms need to go beyond binary thresholds to probabilistic multivariate decision boundaries that can alert farm experts on likelihood measures across potential conditions while highlighting key differentiating factors. Expert systems can additionally suggest hypothesis tests by varying input parameters. Integrating distributed sensor data across farms with historical epidemiological databases, weather projections and veterinary domain expertise can significantly improve predictive situational awareness. Blockchain enabled livestock health ledgers may also incentivize sharing of instrumentation data while securing privacy. Ultimately a network of connected diagnostic labs and care facilities covering rural regions could truly realize the vision of data driven veterinary medicine empowered by universal digital platforms tailored to the specific needs of sheep farms [33].

The instrumented health analytics platform proposed here for individual sheep monitoring represents just the first step in this ambitious roadmap for digital transformation of livestock management practices globally. Significant cross-disciplinary research across sensors, microfluidics, connectivity, analytics, and animal science is essential to address limitations in the current system design. However, with exponentially improving capabilities across these domains driven by commercial IT ecosystems, the solutions outlined in this paper can form the foundation for scalable precision livestock farms of the future [34]. The proposed convergence can thus pave the path towards higher productivity, profitability, and sustainability in global animal husbandry - thereby improving food safety and access in societies worldwide [35], [36].

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