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Utilizing Physiological Metrics and Change Point Analysis for Real-Time Livestock Health Monitoring

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ABSTRACT

Objective: This study introduces a smart ear tag system for real-time monitoring of cattle health, integrating physiological metrics such as body temperature, heart rate, and oxygen saturation (SpO2) with Change Point Analysis (CPA) to detect state changes. **Materials and Methods:** The system was tested over a 7-day period on 10 cattle, monitoring health metrics continuously. CPA was applied to identify synchronized changes in the monitored parameters. The system's performance was evaluated based on its ability to detect potential health status changes while maintaining reliability and specificity. **Results:** The system successfully identified synchronized state changes in one animal, flagging a potential health issue, while showing no significant changes in the other nine animals. This indicates the system's capability to differentiate between normal variability and significant health-related changes. **Conclusion:** The proposed smart ear tag system demonstrates significant potential for Precision Livestock Farming. By integrating multiple physiological metrics and advanced analysis, it offers a reliable framework for improving animal welfare and enabling early disease detection.

Keywords: Livestock Health Monitoring, Digital Technologies in Livestock Farming, Change Point Analysis, Body Temperature, Heart Rate, Oxygen Saturation.

Fizyolojik Metrikler ve Değişim Noktası Analizi Kullanılarak Gerçek Zamanlı Hayvan Sağlığı İzleme

ÖZ

Amaç: Bu çalışma, vücut sıcaklığı, kalp atış hızı ve oksijen doygunluğu (SpO2) gibi fizyolojik metrikleri Değişim Noktası Analizi (CPA) ile entegre ederek, sığır sağlığının gerçek zamanlı izlenmesi için bir akıllı kulak etiketi sistemi sunmaktadır. **Gereç ve Yöntem:** Sistem, 7 gün boyunca 10 sığır üzerinde test edilerek sağlık metrikleri sürekli olarak izlenmiştir. İzlenen parametrelerdeki eş zamanlı değişiklikleri tespit etmek için CPA uygulanmıştır. Sistemin performansı, potansiyel sağlık durumu değişikliklerini tespit etme yeteneği ve güvenilirlik ile özgüllük açısından değerlendirilmiştir. **Bulgular:** Sistem, bir hayvanda eş zamanlı durum değişikliklerini başarıyla tespit ederek potansiyel bir sağlık sorunu işaret ederken, diğer dokuz hayvanda önemli bir değişiklik göstermemiştir. Bu durum, sistemin normal değişkenlik ile sağlıkla ilgili önemli değişiklikleri ayırt etme yeteneğini göstermektedir. **Sonuç:** Önerilen akıllı kulak etiketi sistemi, Hassas Hayvancılık Yönetimi için önemli bir potansiyele sahiptir. Çoklu fizyolojik metriklerin entegrasyonu ve ileri analiz yöntemleri sayesinde hayvan refahını artırmak ve hastalıkların erken teşhisini sağlamak için güvenilir bir çerçeve sunmaktadır.

Anahtar Kelimeler: Hayvan Sağlığı Izleme, Dijital Teknolojilerle Hayvancılık, Değişim Noktası Analizi, Vücut Sıcaklığı, Kalp Atış Hızı, Oksijen Doygunluğu.

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INTRODUCTION

Precision livestock farming (PLF) has revolutionized animal health monitoring by integrating sensor technologies and advanced data analytics. These systems enable continuous and real-time monitoring of livestock, addressing critical challenges in animal welfare, early disease detection, and sustainable farming practices (Besler et al., 2024 and Handa et al., 2022). Livestock health plays a pivotal role in ensuring productivity and economic efficiency, as physiological changes often precede visible signs of illness. Parameters such as body temperature, heart rate, and oxygen saturation (SpO2) provide essential insights into the health and well-being of animals (Halachmi et al., 2019 and Hammer et al., 2016).

The use of sensors in livestock monitoring has evolved significantly, offering non-invasive methods for tracking vital signs. Body temperature is a critical metric for detecting conditions such as fever or estrus, while heart rate serves as an indicator of stress, metabolic activity, and cardiovascular health(Neethirajan et al., 2018 and Nie et al., 2020). SpO2, often overlooked in livestock, provides valuable information on respiratory efficiency and oxygenation, which are crucial in detecting pulmonary or circulatory issues (Rahman et al., 2018 and Shahriar et al., 2016).

Despite advancements in PLF technologies, studies have predominantly focused on these parameters individually, leaving a gap in comprehensive, multi-metric monitoring approaches (Besler et al., 2024 and Tzanidakis et al., 2023). The integration of multiple physiological parameters offers a holistic understanding of animal health, enabling early detection of stressors and illnesses (Zhang et al., 2020 and Peschel et al., 2022). Temperature and heart rate are widely studied early indicators of disease in pigs (Jorquera-Chavez et al., 2020), poultry (He et al., 2022), sheep (Chevalier et al., 2023), calves (Lowe et al., 2019) and dairy cattle (Kim et al., 2019). Recent developments in Change Point Analysis (CPA) further enhance the capability to identify significant shifts in time-series data, making it an ideal tool for livestock health monitoring (Saint-Dizier et al., 2012 and Peel, 2020).

In this study, we hypothesize that integrating body temperature, heart rate, and SpO2 measurements into a single monitoring system can provide a comprehensive and real-time assessment of livestock health. The purpose of this research is to develop and validate a smart ear tag system that employs advanced sensor technology and CPA to detect physiological changes. By simultaneously monitoring these three critical parameters, we aim to ***detect state changes*** caused by key factors such as ***estrus, early signs of illness***, and ***environmental stress***. By capturing such diverse state changes, the smart ear tag system not only enhances health monitoring but also supports decision-making in areas like breeding, disease management, and welfare optimization, aligning with the goals of sustainable PLF.

MATERIALS AND METHODS

Study design and ethical statement

This study was conducted to develop and validate a smart ear tag system for continuous monitoring of physiological parameters in cattle, including body temperature, heart rate, and SpO2. Ethical approval for the study was obtained from the Mehmet Akif Ersoy University Animal Experiments Local Ethics Committee (Approval no: 1203). All experimental procedures adhered to ethical guidelines for the care and use of animals in research.

Development of the smart ear tag system

The smart ear tag system is designed to enable continuous monitoring of critical physiological parameters in cattle, specifically body temperature, heart rate, and SpO2 (oxygen saturation). The hardware components included the LM35 temperature sensor (Texas Intruments, United States of America), selected for its precision in detecting subtle temperature variations, and the MAX30100 (Analog Devices, United States of America) sensor module, which integrates optical technology to measure heart rate and SpO2. These sensors were paired with an Arduino microcontroller (Figure 1), chosen for being open-source hardware, its compatibility with multiple modules and its ease of programming, making it an ideal choice for real-time data acquisition and processing.

To ensure portability and minimal weight, the system was powered by a compact, rechargeable lithium-ion battery, while a MicroSD card module was used to store the collected data in CSV (Comma-seperated values) format for seamless transfer and analysis. The entire assembly was encased in a durable, waterproof shell to protect it from environmental factors such as moisture, dust, and physical impacts.

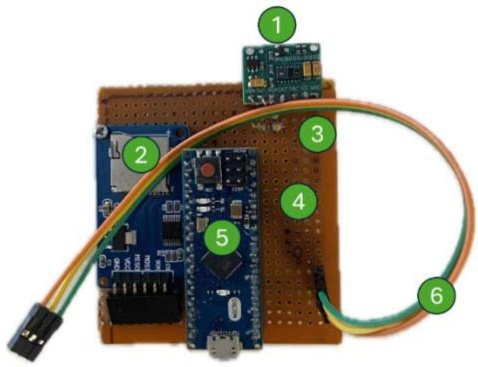

Figure 1. The smart ear tag system. Components: (1) MAX30100 sensor module, (2) Micro SD, (3) 4.7 Ohm Resistor, (4) Perforated PCB (Protoboard), (5) Arduino Microcontroller, (6) LM-35 Temperature Sensor

The software development process focused on programming the Arduino microcontroller using the Arduino IDE, with code written in C++ to handle sensor data acquisition, storage, and error management. The data were formatted into CSV files, including timestamps with second-level accuracy, to facilitate post-processing and analysis. The assembly process began with prototype testing on a breadboard, allowing iterative debugging of hardware connections and software logic. Once the prototype passed initial tests, the components were transferred to a perforated printed circuit board (PCB) and soldered to create a compact and durable system. The PCB was then mounted within the protective casing, designed with ports for changing batteries and data extraction.

Data collection

The ear tag system was tested on 10 Holstein cows in their early lactation period, between 2 and 4 ages. The smart eartag soldered onto a standard ear tag and they were securely attached using a standard ear tag applicator. Data were collected twice daily for one-hour sessions over a 7-day period. During each session, the tag continuously recorded body temperature, heart rate, and SpO2, and stored the data in CSV format. Data files were extracted and transferred to a computer at the end of each session for further analysis.

Implementation

The analysis was carried out using Python's *ruptures* library (Truong et al., 2018), which provides robust support for multiple cost functions and optimization algorithms. The process began with a thorough preprocessing of the physiological time series data. Using the *pandas library*, the data were loaded and cleaned to remove any missing or outlier values that could compromise the analysis. This step was crucial to ensure data integrity and reliability.

For segmenting the data, the "least squares" cost function was applied. This function calculates the variance within each segment, effectively detecting shifts in both mean and variance across the time series. The dynamic programming algorithm available in the *ruptures library* was then employed, enabling precise identification of change points within the data.

Finally, the results of the segmentation were visualized using the *matplotlib library*. The detected change points were plotted against the original time series data, with each change point clearly marked. This visual representation allowed for the validation of segmentation accuracy, ensuring that the detected changes aligned with expected physiological shifts. This integrated approach provided a comprehensive framework for analyzing and interpreting the physiological data effectively.

Statistical analysis

Collected data were analyzed using CPA (Chen et al., 2000) a statistical method designed to detect abrupt changes in the statistical properties of a time series, such as mean, variance, or distribution. CPA is particularly useful in identifying *transitions in physiological data* over time, making it ideal for real-time health monitoring in livestock. *Mathematical Framework of CPA* is as follows:

Let $X = \{x_1, x_2, \dots, x_n\}$ represent the time series data for a physiological parameter (e.g., body temperature, heart rate, or SpO_2). The objective of CPA is to identify points τ where the statistical characteristics of X change. Specifically, these change points split the time series into segments $X_1, X_2, \dots, X_k$, where each segment is statistically homogeneous.

Model Assumption: CPA assumes that for ith segment $X_i = \{x_{\tau_{i-1}+1}, \dots, x_{\tau_i}\}$

$$x_t \sim F_i \quad \forall t \in [\tau_{i-1}+1, \tau_i]$$

where F_i represents the distribution of X_i. The change points $\tau_1, \tau_2, \dots, \tau_k$ are determined such that $F_i \neq F_{i+1}$

Cost function: A cost function $C(X_i)$ quantifies the dissimilarity within a segment. The goal is to minimize the total cost:

$$Total\ Cost = \sum_{i=1}^{k} C(X_i)$$

subject to constraints on the number or location of change points. For example, $C(X_i)$ could be based on changes in mean, variance, or both.

To detect changes in the time series data accurately, various optimization algorithms were employed. Dynamic Programming was utilized to minimize the cost function over all possible segmentations, ensuring a globally optimal solution. This algorithm is computationally intensive but highly precise in identifying change points. For scenarios requiring faster computation, Binary Segmentation was considered. This iterative approach splits the data into segments based on the largest detected change, offering a quicker but approximate solution. These algorithms formed the foundation for implementing CPA in this study.

Ethical considerations

Ethics committee approval for this study was obtained from Mehmet Akif Ersoy University Animal Experiments Local Ethics Committee (Decision No: 1203, Decision Date: 27.10.2023). This study was conducted by the Declaration of Helsinki.

RESULTS

The smart ear tag system successfully monitored body temperature, heart rate, and SpO2 in cattle over a 7-day period. Among these animals, significant changes were detected only in one individual, while no state changes were observed in the remaining nine. The results demonstrate the system's capability to detect physiological deviations while maintaining specificity and avoiding false positives.

Individual parameter analysis

The graph (Fig. 2) illustrates significant state changes in SpO2 levels over time. In the initial phase (0-75), two sharp drops followed by a rapid spike above 100% suggests a problem with recording or environmental effects on sensors. Between 75 and 200, SpO2 levels stabilize, indicating homeostasis and a balanced physiological state. However, after 200, the data reveal a new state, where SpO2 levels remain consistent but slightly shifted, suggesting either long-term adaptation or a lasting change in the animal's physiological condition.

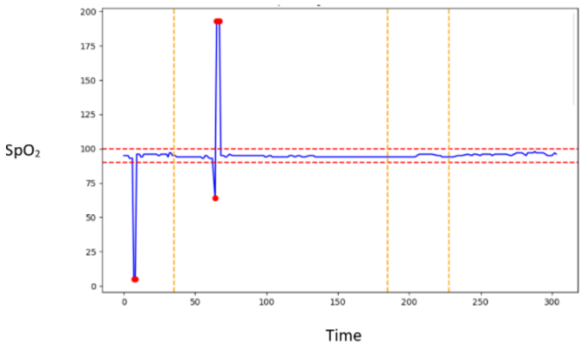

Figure 2. SpO_2 levels and detected state shifts over time.

The graph (Fig. 3) illustrates the temperature variations over time, highlighting significant state changes rather than focusing solely on the temperature values themselves. Since temperature is measured from the ear, environmental factors such as ambient temperature, humidity, or direct exposure can influence the readings, leading to fluctuations. However, CPA is designed to detect shifts in the state of the temperature pattern, providing deeper insights into potential physiological or systemic changes. In phase *0-200*, The temperature shows fluctuations but generally remains within a lower range, likely reflecting a stable physiological state with minor environmental influences. After the marked state change between 200-250, the temperature readings stabilize within a new range, despite occasional anomalies. This shift suggests the animal has transitioned to a new physiological state, potentially as an adaptive response to internal or external factors. The graph (Fig. 4) depicts heart rate variations over time, focusing on state changes rather than isolated anomalies. Heart rate is a highly dynamic parameter, influenced by both physiological factors (e.g., stress, activity levels) and environmental stimuli. CPA identifies shifts in the overall state of heart rate patterns, providing insights into underlying physiological transitions. In phase *0-200*, heart rate readings are moderately stable with occasional spikes, likely reflecting minor stressors or activity-related changes. The overall state suggests a balance between baseline heart activity and short-term variations. Following the marked state change between 200-250, heart rate patterns stabilize within a new range. While occasional anomalies persist, the general trend indicates a shift to a new physiological equilibrium, possibly as an adaptive response to the earlier stress or environmental factors.

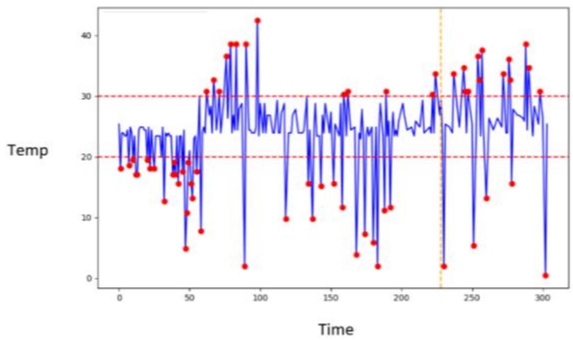

Figure 3. Body temperature variations and detected state shift.

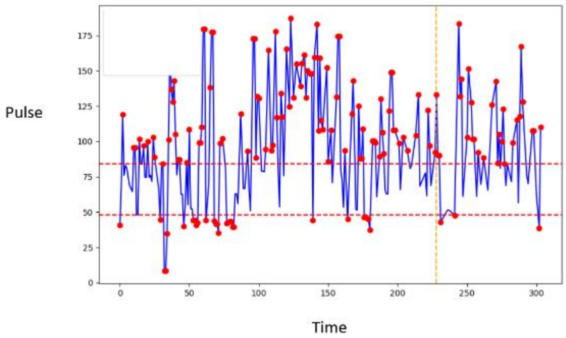

Figure 4. Heart rate variations and detected state shifts.

Multi-Parameter Change Detection

The combined analysis of SpO2, body temperature, and heart rate reveals a synchronized state change occurring around the same time period, particularly between 200th and 250th time unit. (It corresponds to approximately 4.5 to 5.5 days in the 7-day measurement period). While each parameter independently shows fluctuations influenced by physiological or environmental factors, the concurrent shift across all three suggests a significant systemic transition. The SpO2 data stabilizes into a new range, indicating a potential adaptation in respiratory efficiency, while body temperature also transitions to a different stable state, possibly reflecting a response to internal or external stressors. Similarly, heart rate variability reduces post-transition, settling into a more consistent pattern.

DISCUSSION

This study introduces a novel smart ear tag system capable of simultaneously monitoring three critical physiological parameters—body temperature, heart rate, and SpO_2—in cattle. By integrating these metrics with CPA, the system offers an innovative approach to detecting state changes in livestock, which are indicative of significant physiological or behavioral transitions, such as estrus or illness.

While extreme changes of SpO2 levels above 100% or below 75% suggests a problem occurred during data recording or transfer, SpO2 levels after time 75 stabilizes and records values coherent with the

optimum values of around 95% (Calcante & Tangorra, 2021).
Cattle's optimum body temperature is between 39.08 and 41.1 degrees Celsius. This reflects core body temperature (Gaughan & Mader, 2014), this study relied on body surface temperatures. Body surface temperature varies greatly between different parts of the body and can be up to 13 degrees Celsius lower then the rectal temperature (Salles et al., 2016). This study's results are coherent with this data with the lower measurements are slightly lower then expected. This suggests ear's surface temperature is effected by ambient temperature more than flanks or legs.
Although the optimum heart rate of cattle is between 55 and 80 (Darwis et al., 2022), it can reach 135 beats per minute during physical activity (Zerbini et al., 1992). Results of this study is coherent with the previous findings with the exception of several spikes in recordings.
Overall coherence of the recordings suggests that this type of a device complementing other PLF instruments would be feasible in farm setting, but further research should focus on spikes and errors in its current readings to improve consistency and reliability. Also, the absence of physical activity information or visual monitoring prevents any solid insights into the reasons behind these state changes. Milking may cause various physiological responses in a cow's body (Hopster et al., 2002). However, in this study, it can be conjectured that the state change is not related to milking, as milking is expected to occur 4 to 10 times within the study timeframe.
The results suggest that the state change observed in the single animal coincided with its known estrus state at the time of application, with the transition detected between 200–250 time units (approximately 4.5 to 5.5 days) likely reflecting its metabolic changes. In contrast, no significant state changes were detected in the other nine cattle. This indicates that the system's ability to detect state changes is closely tied to the timing of physiological transitions, emphasizing the importance of synchronized monitoring with known reproductive cycles.
The ability to monitor body temperature, heart rate, and SpO_2 simultaneously provides a multi-dimensional perspective on cattle health. These parameters are highly interdependent and sensitive to systemic changes; for example, estrus often induces fluctuations in body temperature, heart rate, and oxygen saturation as part of the metabolic and hormonal shifts associated with reproduction. By detecting synchronized state changes across these parameters, the system reduces the likelihood of overlooking critical transitions, which single-metric systems might miss.
These findings contribute to scientific efforts in the PLF concept. PLF aims to increase yields, production, and welfare (Cox, 2003) and strives to achieve environmental, social, and economic sustainability (Vranken & Berckmans, 2017).While there are challenges about real-time measurements (Neethirajan, 2023) or data management (Halachmi et al., 2019) PLF concept will meet these targets by improvements on the devices used such as smaller or easier to install devices which are also more accurate and efficient (Michelena et al., 2024).
Prior research, such as (Lovarelli et al., 2020 and Zhang et al., 2020), emphasized environmental or behavioral monitoring but lacked the integration of real-time physiological metrics. Similarly, (Nie et al., 2020) discussed the challenges of heart rate monitoring without addressing multi-metric synchronization. (Lee & Seo, 2021) emphasized inconsistency as an area of improvement. This study addresses these gaps by combining physiological data into a unified framework, validated through CPA, to deliver more comprehensive insights into livestock health dynamics.

Study Limitations

While the findings demonstrate the system's potential, the small sample size limits the generalizability of the results. Future studies will focus on larger populations to validate these findings across diverse physiological conditions and reproductive cycles. Integrating external environmental data and applying machine learning techniques could also enhance the system's predictive accuracy, allowing for broader applications in PLF.

CONCLUSION

This study introduces a pioneering approach to livestock health monitoring through the integration of multi-metric physiological data and advanced analytical techniques. By employing body temperature, heart rate, and oxygen saturation (SpO2) as key parameters and detecting synchronized state changes using CPA, the proposed smart ear tag system addresses critical challenges in PLF. The ability to monitor multiple metrics simultaneously ensures a more comprehensive understanding of livestock health, which is vital for early detection of diseases and effective animal welfare management.
The results highlight the system's robustness in distinguishing between normal physiological variability and significant state changes, underscoring its reliability and precision. These attributes are essential for ensuring that livestock management practices are proactive and aligned with the goals of sustainable farming. Additionally, the system's capacity to identify systemic changes, such as those associated with estrus or stress, further validates its potential to support decision-making processes in breeding, health management, and overall productivity optimization.
In conclusion, this research represents a significant step forward in leveraging digital technologies for the agricultural sector. By providing a scalable and practical tool for real-time health monitoring, the smart ear tag system supports the transition towards data-driven and sustainable livestock management.

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Conflict of Interest
The author declares no potential conflicts of interest with respect to the research, authorship and/or publication of this article.

Author Contributions
Plan, design: B.C., M.M.D**; Material, methods and data collection:** B.C., M.M.D, H.B.A., H.I.E**; Data analysis and comments:** B.C., H.B.A**; Writing and corrections:** B.C., M.M.D, H.B.A.**.**

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Ethical Approval
Institution: Mehmet Akif Ersoy University Animal Experiments Local Ethics Committee
Date: 27.10.2023
Approval no: 1203

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