Airborne Vision-Based Remote Sensing Imagery Datasets From Large Farms Using Autonomous Drones For Monitoring Livestock

Kaya Kuru[1], Darren Ansel[1] and David Jones[1]

[1] School of Engineering and Computing, University of Central Lancashire, Preston PR1 2HE, U.K.

Abstract

Livestock have high economic value and monitoring of them in large farms regularly is a labour-intensive task and costly. The emergence of smart data on individual animals and their surroundings opens up new opportunities for early detection and disease prevention, better animal care and traceability, better sustainability and farm economics. Precision Livestock Farming (PLF) relies on the constant and automated gathering of livestock data to support the expertise and management decisions made by farmers, vets, and authorities. The high mobility of UAVs combined with a high level of autonomy, sensor-driven technologies and AI decision-making abilities can provide many advantages to farmers in exploiting instant information from every corner of a large farm. The key objectives of this research are to i) explore various drone-mounted vision-based remote sensing modalities, particularly, visual band sensing and a thermal imager, ii) develop UAV-assisted autonomous PLF technologies and ii) collect data with various parameters for the researchers to establish further advanced AI-based approaches for monitoring livestock in large farms effectively by fusing a rich set of features acquired using vision-based multi-sensor modalities. The collected data suggest that the fuse of distinctive features of livestock obtained from multiple sensor modalities can be exploited to help farmers experience better livestock management in large farms through PLF.

Keywords: Precision Livestock Farming (PLF); livestock health monitoring; livestock management, unmanned aerial vehicles (UAV), autonomous drones, thermal imagery; active RFID, livestock image processing.

1. INTRODUCTION

The emergence of smart data on individual animals and their surroundings opens up new opportunities for early detection and disease prevention, better animal care and traceability, better sustainability and farm economics. Precision Livestock Farming (PLF) is the development of smart animal farming through the use of sensors and information technologies to improve animal health, animal welfare and production, and to reduce the impact on the environment [1]. PLF relies on the constant and automated gathering of livestock data to support the expertise and management decisions made by farmers, vets, and authorities. UAV-assisted smart farming within large farms has gained momentum in managing large farms effectively by avoiding high costs and increasing the quality of monitoring. To this end, the high mobility of UAVs combined with a high level of autonomy, sensor-driven technologies and AI decision-making abilities can provide many advantages to farmers in exploiting instant information from every corner of a large farm. The key objective of this research is to i) explore various drone-mounted vision-based remote sensing modalities, particularly, visual band sensing and a thermal imager and ii) collect data with various parameters for the researchers to establish further advanced AI-based approaches to monitor livestock in large farms effectively by fusing the acquired multi-sensor datasets. These advanced approaches, enabling accurate detection of animals and health anomalies, can help farmers to take targeted or preemptive action, and improve the health, welfare, and productivity of their livestock. In today's dairy world, farm sizes are growing larger and larger and the larger the farms, the more difficult it is to manage them using the conventional farm management approaches [2]. To successfully operate any large farm, effective livestock management is crucial and monitoring them in large farms is a labour-intensive task and costly [1]. Smart farming with livestock is an emerging high-tech area focused on automating production and, thus, reducing the cost of the human (manual) effort involved in daily tasks, which makes animal welfare an increased concern [3]. Vehicles are becoming increasingly automated by taking on more and more tasks [4], [5] under improving intelligent control systems equipped with enhancing sensor technologies and Artificial Intelligence (AI) techniques [6], [7], [8]. Autonomous Uninhabited Aerial Vehicles (UAVs) (A-UAVs), as flying autonomous robots, with self-learning and self-decision-making abilities by executing non-trivial sequences of events with decimetre-level accuracy based on a set of rules, control loops and constraints using dynamic flight plans involving autonomous take-off and landing are taking their indispensable parts with little or no human in the loop [9], [10] to accomplish various automated tasks [11], [12], [13], [14], [15], [16], [17]. Precision Livestock Farming is one of the most promising applications showing the benefits of using drones [18] where a lack of human element in the farming industry is becoming evident [19]. Remote detection and counting is safe, cost-effective and could be easily and frequently repeated, providing prompt information about livestock's population size and their instant location [20]. The key objectives of this research are to i) explore various drone-mounted vision-based remote sensing modalities, particularly, visual band sensing and a thermal imager, ii) develop UAV-assisted autonomous PLF technologies and ii) collect data with various parameters for the researchers to establish advanced AI-based approaches for monitoring livestock in large farms effectively by fusing a rich set of features acquired using vision-based multi-sensor modalities. UAV-mounted IoT technologies equipped with AI-based approaches, enabling fully automated decision support tools can detect changes in livestock behaviour and their physiological conditions for providing early indications of potential disease outbreaks or other stress events and allowing farmers to take targeted or preemptive action, and improve the health, welfare, and productivity of their livestock.

Figure 1: Main interface of the application being developed in this research

2. METHODS

The University of Central Lancashire (UCLan) facilitates the research and development of drone technology and AI software, provides drones, and assists with integrating drone inspections into the farmer's workflow. In this research, an automated drone solution (Fig. 1) with a cross-discipline approach within the concept of Automation of Everything and Internet of Everything [21], [22] has been deployed to collect datasets from large farms in an automated manner using vision-based sensor modalities involving both standard visual band sensing and a thermal imager. The images/videos are aimed to be processed using artificial intelligence (AI) based software to detect stock numbers, and individual animal temperatures to indicate the presence of infection or stage in the fertility cycle. A number of supervised and unsupervised [23] Machine Learnineg (ML) and Deep Learning (DL) techniques can be examined through data fusion based on the features of the datasets (videos, images) collected in both visible band wavelengths and thermal imagery. As an essential physiological index, animal body surface temperature can be used to accurately evaluate the physiological state of animals under stress, fertility, welfare, metabolism, health, and disease [24]. An AI-based application using an ensemble of AI techniques can be highly beneficial to performing image classification and clustering to achieve the objectives of animal analytics using the datasets provided in this research. The onboard IoT platforms enable the drone to be operated consistently and reliably by automating many key functions that could otherwise be subject to human error. The developed applications by the research community using the datasets provided in this research help report any abnormal situation to the farmers to improve the adverse conditions. The camera models by which datasets were collected are shown in Figs. 2, 3, and 4. The properties of these models are explicated below with example images acquired from various large farms. Acquired datasets from the aforementioned sensor modalities are placed in the supplementary materials of this document.

Figure 2: DJI Zenmuse H20T

Figure 3: DJI Zenmuse L1

a) b)

Figure 4: a) Drone (Matrice 300 RTK) with DJI Zenmuse L1; b) Drone (Mavic 2) with FC2403 camera

a. H20T

H20T with quad-sensor solution provides four sensors – I) a 20 MP Zoom Camera (23× Hybrid Optical Zoom, 200× Max Zoom, 20 MP 1/1.7” CMOS Sensor, Video Resolution: 4K/30fps), ii) a 12 MP Wide Camera (Equivalent Focal Length: 24mm, DFOV: 82.9°, 12 MP 1/2.3” CMOS Sensor), iii) 1200 m Laser Rangefinder (LRF) (Range: 3 m – 1200 m, Accuracy: ± (0.2 m + D×0.15%)), and iv) a 640 X 512 px Radiometric Thermal Camera (DFOV: 40.6°, Resolution: 640×512, Frame Rate: 30fps, Thermal Sensitivity: ≤ 50mk@f1.0 (NEDT)) – in one package at a time. An integrated laser rangefinder (LRF) measures the distance to an object at up to 1200 m away. A powerful, integrated payload that unleashes advanced intelligent capabilities for DJI’s industrial drone platforms.

Figure 5: Image from 20 MP Zoom Camera

Figure 6: Image from 12 MP Wide Camera

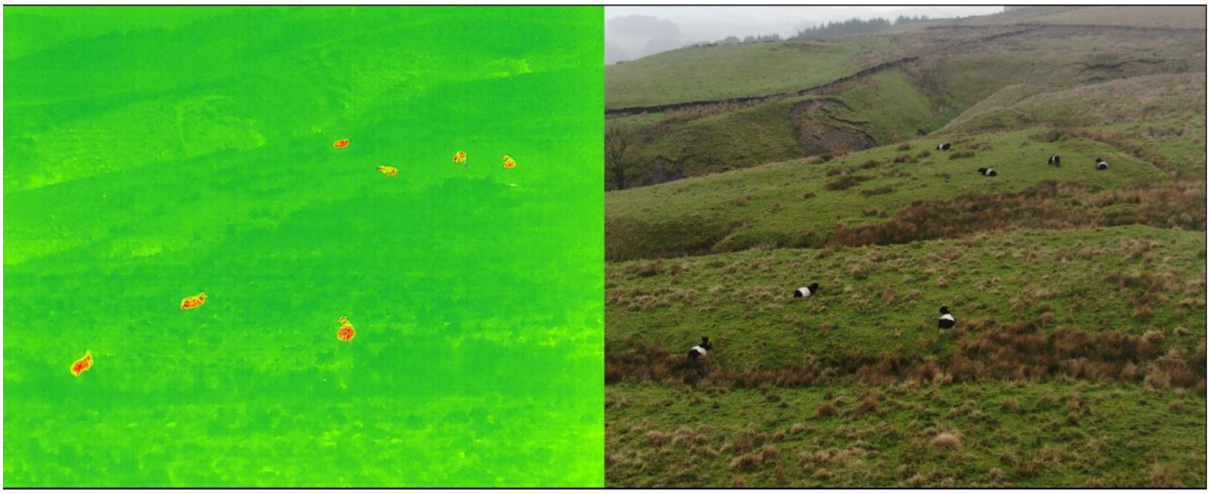

Figure 7: Image from 1200 m LRF

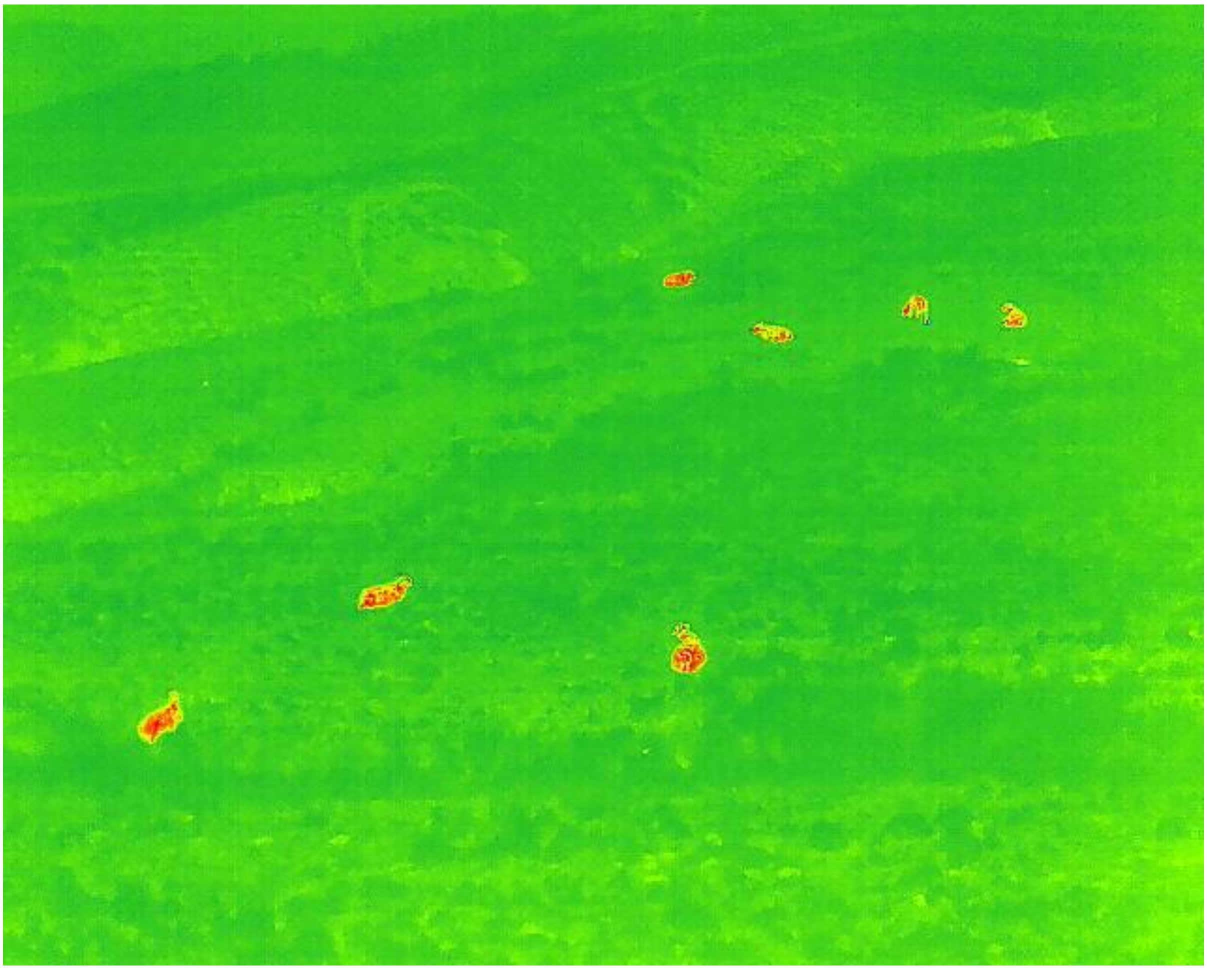

Figure 8: Image from 640 X 512 px Radiometric Thermal Camera

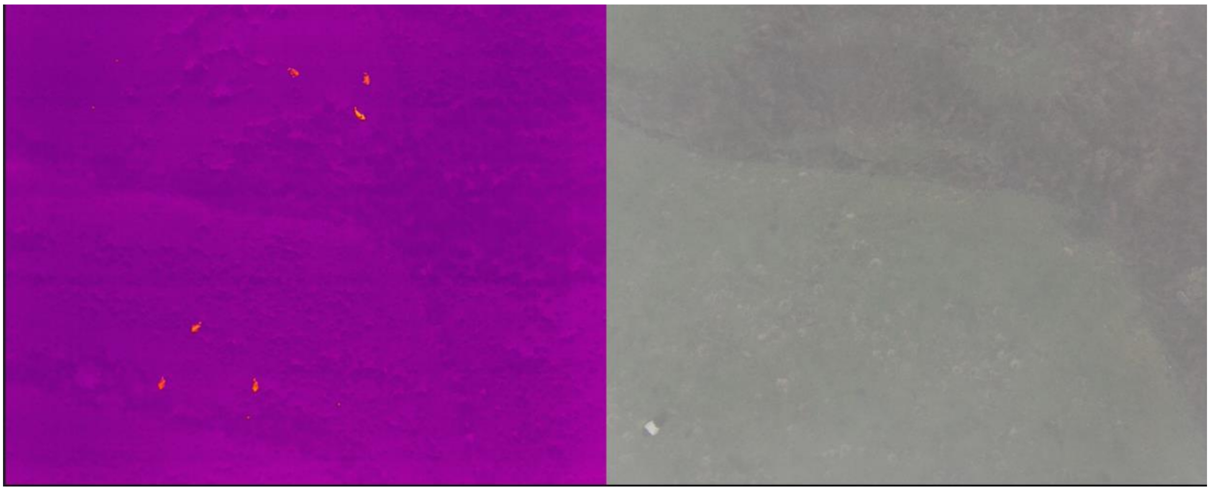

Figure 9: Use of different planner: Image from 1200 m LRF

Figure 10: Use of different planner: Image from 1200 m LRF

Figure 11: Use of different planner: Image from 1200 m LRF

Figure 12: Use of different planner: Image from 1200 m LRF

Figure 13: Use of different planner: Image from 1200 m LRF

Figure 14: Use of different planner: Image from 1200 m LRF

Figure 15: Use of different planner: Image from 1200 m LRF

Figure 16: Use of different planner: Image from 1200 m LRF

The headings of the images have altitude information as well as latitude and longitude information stored in the container of the metadata of images to stitch the images to form the whole farm and perform the monitoring accordingly without taking the same animal into processing multiple times. More datasets will be uploaded as the project progresses for the researchers to construct their applications with trained classifier models using supervised ML and/or Deep Learning (DL) techniques.

b) Mavic 2 camera (FC2403)

The camera is composed of two sensing abilities, namely, thermal sensing and standard RGB sensing. Readers are referred to https://www.dji.com/uk/mavic-2-enterprise/specs for further specifications.

Figure 17: Image from FC2403

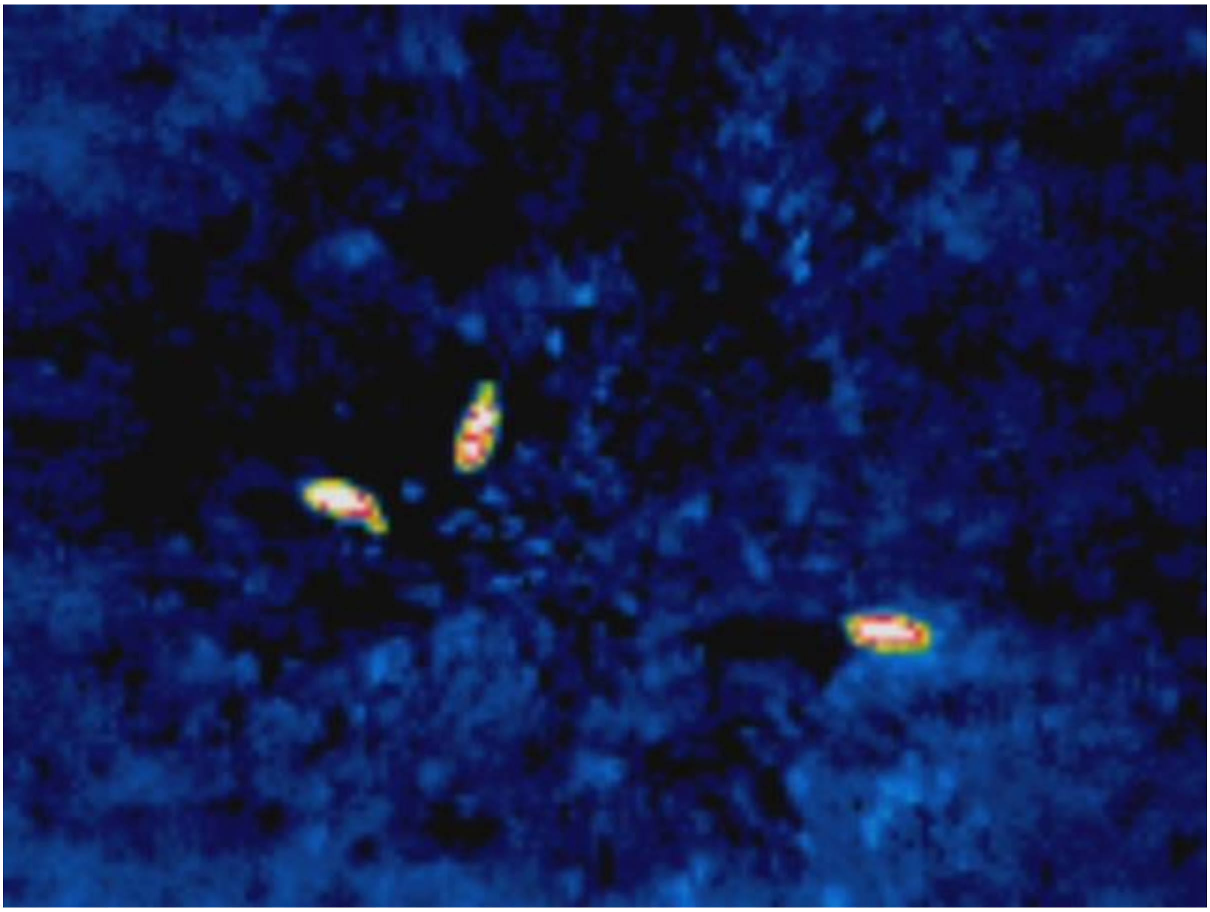

Figure 18: Image from FC2403 using thermal sensing

c) DJI Zenmuse L1

The Zenmuse L1 integrates a Livox Lidar module, a high-accuracy IMU, and a camera with a 1-inch CMOS on a 3-axis stabilized gimbal. When used with Matrice 300 RTK and DJI Terra, the L1 forms a solution that provides real-time 3D data, efficiently capturing the details of complex structures and delivering accurate 3D models. Data can be visualised as the drone flies in an autonomous mode using the Livox Lidar module. This module provides i) Frame Lidar with up to 100% effective point cloud results, ii) Detection Range: 450m (80% reflectivity, 0 klx) / 190 m (10% reflectivity, 100 klx), ii) Effective Point Rate: 240,000 pts/s, iv) Supports 3 Returns, and v) Non-repetitive scanning pattern, Repetitive scanning pattern. With Zenmuse L1, High-accuracy IMU can be acquired using the vision sensor for positioning accuracy by fusing GNSS, IMU, and RGB data. This property can be highly useful for stitching consecutive images to form the whole farm. Readers are referred to https://enterprise.dji.com/zenmuse-l1 for detailed information about this sensor modality. We will be uploading more datasets using this modality.

3. RESULTS

The portion of the electromagnetic spectrum extending from approximately 0.1 to 100mm, (the visible and the infrared spectrum) is named thermal radiation [25]. Thermal cameras collect infrared radiation emitted by the surface, convert it into electrical signals and create a thermal image showing the body's superficial temperature distribution [25]. In this process, each colour expresses a specific temperature range, related to the defined scale. Infrared thermal imaging (ITI) has high-temperature sensitivity and spatial resolution, uses a non-contact method, and can quickly and efficiently collect animal surface temperature without direct physical contact with animals [26]. This sensor technology can be used to evaluate several different clinical syndromes not only in the diagnosis of inflammation but also to monitor the progression of healing [27]. The collected data suggest that the fuse of distinctive features of livestock obtained from multiple sensor modalities can be exploited to help farmers experience better livestock management in large farms. The datasets regarding the animal body heat signatures obtained from the thermal imagery show promising results in detecting disease-related cases. Using drones with highly automated flights provides on-demand accurate information to the farmer that enables early interventions with high-accuracy detection and classification of livestock should an animal go missing or need attention on the grounds of animal health and welfare. The research demonstrates how highly integrated technologies with drones can help the farming industry to overcome the challenging issues in the management of livestock, particularly, health monitoring of livestock in very large farms in an eco-friendly and sustainable way. The benefits of autonomous, AI-based, UAV-assisted IoT applications in the management of livestock large farms, by providing farmers with more efficient and accurate ways of gathering data on animal health, movement patterns, and behaviour, can i) reduce farmers' time spent on covering large spaces more efficiently and quickly than traditional methods by using drones for livestock inspection, ii) Improve farm productivity by quickly and accurately counting all animals and monitoring their welfare, and iii) reduce reliance on fossil fuels using battery-operated drones contributing to a lower carbon footprint.

4. CONCLUSION

With the expanding global population, there is now an urgent need to produce more food, more efficiently with the available existing finite resources [28]. Efficient, affordable, and scalable livestock management solutions play an increasingly important role in modern farming, as the number of farms decreases, but the number of livestock on each increases [29] with the growing trend of increasing farm sizes [30]. Annually, over 2.5 million US cattle valued at $1.5 billion die from diseases [31]. This high rate of death toll caused by various diseases necessitates the need for effective livestock health management that paves the way for disease detection at an early stage [32]. PLF aims to provide farmers with effective tools equipped with high technologies in livestock management while improving the welfare of animals paving the way for satisfying the demands of consumers in a sustainable way. UAV-based IoT technologies are now becoming more accessible and affordable for farmers, allowing them to gather valuable data more efficiently and make better business decisions. While drones are usually used in agriculture for crop spraying, mapping, and crop monitoring, their application in monitoring animal health and livestock is a highly promising research avenue in the agriculture industry. This research is a productivity and sustainability-focused pilot to investigate and demonstrate how drones and artificial intelligence software can provide a better way to regularly inspect animals on a large farm to avoid high costs and increase monitoring quality. The use of sensors for continuous real-time monitoring helps reduce the time-consuming human observation, making PLF day-by-day more important and sustainable concerning the need for an expensive workforce [33]. The integration of UAVs embedded with IoT applications that are equipped with sensor-driven technologies can help survey large farms regularly in a timely manner with advanced AI tools, improve the early diagnosis of livestock diseases and reduce disease-related deaths significantly. To this end, the high mobility of UAVs combined with a high level of autonomy and AI decision-making abilities can provide many advantages to farmers in exploiting instant information from a large farm. Not only does the use of drones reduce our reliance on fossil-fuelled vehicles, but there are also labour cost savings from a reduced labour requirement so we can allocate more time and valuable resources to other tasks that will boost productivity. The livestock datasets provided, acquired from large farms in this research, using various vision-based sensor modalities can help researchers to develop PLF by fusing the distinctive features of livestock, which paves the way for developing effective AI-based approaches for farmers to experience better livestock management in large farms.

REFERENCES

[1] Kuru, K., Ansell, D., and Jones, D. (2023) Intelligent Airborne Monitoring of Livestock Using Autonomous Uninhabited Aerial Vehicles. In: The 11th European Conference on Precision Livestock Farming, 09-12 September 2024, Bologna, Italy.

[2] Papageorgiou, G., Porgouris, K., Efstathiades, A., & Papageorgiou, G. A. (2020). Evaluating the Development of Activity Monitoring Systems for Small Scale Dairy Farms. In 2020 7th International Conference on Energy Efficiency and Agricultural Engineering. 2020 7th International Conference on Energy Efficiency and Agricultural Engineering (EE&AE). IEEE. https://doi.org/10.1109/eeae49144.2020.9278987

[3] Jukan, A., Carpio, F., Masip, X., Ferrer, A. J., Kemper, N., & Stetina, B. U. (2019). Fog-to-Cloud Computing for Farming: Low-Cost Technologies, Data Exchange, and Animal Welfare. In Computer (Vol. 52, Issue 10, pp. 41–51). https://doi.org/10.1109/mc.2019.2906837

[4] Kuru, K. *et al.* (2023). Toward Mid-Air Collision-Free Trajectory for Autonomous and Pilot-Controlled Unmanned Aerial Vehicles. In IEEE Access (Vol. 11, pp. 100323–100342). https://doi.org/10.1109/access.2023.3314504

[5] Kuru, K. (2021). Planning the Future of Smart Cities With Swarms of Fully Autonomous Unmanned Aerial Vehicles Using a Novel Framework. In IEEE Access (Vol. 9, pp. 6571–6595). https://doi.org/10.1109/access.2020.3049094

[6] Kuru, K. (2023). Sensors and Sensor Fusion for Decision Making in Autonomous Driving and Vehicles. Sensors.

[7] Kuru, K. (2022). TrustFSDV: Framework for Building and Maintaining Trust in Self-Driving Vehicles. In IEEE Access (Vol. 10, pp. 82814–82833). https://doi.org/10.1109/access.2022.3196941

[8] Kuru, K. *et al*. (2021). A Framework for the Synergistic Integration of Fully Autonomous Ground Vehicles With Smart City. In IEEE Access (Vol. 9, pp. 923–948). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/access.2020.3046999

[9] Kuru, K. (2021). Conceptualisation of Human-on-the-Loop Haptic Teleoperation With Fully Autonomous Self-Driving Vehicles in the Urban Environment. In IEEE Open Journal of Intelligent Transportation Systems (Vol. 2, pp. 448–469). https://doi.org/10.1109/ojits.2021.3132725

[10] Kuru, K. *et al*. (2023). AITL-WING-HITL: Telemanipulation of autonomous drones using digital twins of aerial traffic interfaced with WING. In IEEE Access (Vol. 11).

[11] Kuru, K. *et al*. (2019). Analysis and Optimization of Unmanned Aerial Vehicle Swarms in Logistics: An Intelligent Delivery Platform. In IEEE Access (Vol. 7, pp. 15804–15831). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/access.2019.2892716

[12] Kuru, K. *et al*. (2023). WILDetect: An intelligent platform to perform airborne wildlife census automatically in the marine ecosystem using an ensemble of learning techniques and computer vision. In Expert Systems with Applications (Vol. 231, p. 120574). https://doi.org/10.1016/j.eswa.2023.120574

[13] Kuru, K. *et al*. (2023). Intelligent airborne monitoring of irregularly shaped man-made marine objects using statistical Machine Learning techniques. In Ecological Informatics (Vol. 78, p. 102285). Elsevier BV. https://doi.org/10.1016/j.ecoinf.2023.102285

[14] Kuru, K., & Ansell, D. A. (2023). Vision-Based Remote Sensing Imagery Datasets From Benkovac Landmine Test Site Using An Autonomous Drone For Detecting Landmine Locations [dataset]. IEEE DataPort. https://doi.org/10.21227/PTSA-QJ43

[15] Kuru, K. *et al*. (2023). Intelligent, automated, rapid and safe landmine and Unexploded Ordnance (UXO) detection using Maggy. IEEE Transactions on Geoscience and Remote Sensing.

[16] Kuru, K. *et al*. (2023). Intelligent automated, rapid and safe landmine and Unexploded Ordnance (UXO) detection using multiple sensor modalities mounted on autonomous drones. IEEE Transactions on Geoscience and Remote Sensing.

[17] Kuru, K. *et al*. (2023). IoTFaUAV: Intelligent remote monitoring of livestock in large farms using Autonomous uninhabited aerial vehicles. In Computers and Electronics in Agriculture.

[18] Bacco, M., Berton, A., Gotta, A., & Caviglione, L. (2018). IEEE 802.15.4 Air-Ground UAV Communications in Smart Farming Scenarios. In IEEE Communications Letters (Vol. 22, Issue 9, pp. 1910–1913). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/lcomm.2018.2855211

[19] Grogan, A. (2012). Smart farming. In Engineering & Technology (Vol. 7, Issue 6, p. 38). Institution of Engineering and Technology (IET). https://doi.org/10.1049/et.2012.0601

[20] Kalmukov, Y., & Evstatiev, B. (2022). Methods for Automated Remote Sensing and Counting of Animals. In 2022 8th International Conference on Energy Efficiency and Agricultural Engineering (EE&AE). 2022 8th International Conference on Energy Efficiency and Agricultural Engineering (EE&AE). IEEE. https://doi.org/10.1109/eeae53789.2022.9831239

[21] Kuru, K., & Yetgin, H. (2019). Transformation to Advanced Mechatronics Systems Within New Industrial Revolution: A Novel Framework in Automation of Everything (AoE). In IEEE Access (Vol. 7, pp. 41395–41415). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/access.2019.2907809

[22] Kuru, K. (2021). Management of geo-distributed intelligence: Deep Insight as a Service (DINSaaS) on Forged Cloud Platforms (FCP). In Journal of Parallel and Distributed Computing (Vol. 149, pp. 103–118). Elsevier BV. https://doi.org/10.1016/j.jpdc.2020.11.009

[23] Kuru, K., & Khan, W. (2018). Novel hybrid object-based non-parametric clustering approach for grouping similar objects in specific visual domains. In Applied Soft Computing (Vol. 62, pp. 667–701). Elsevier BV. https://doi.org/10.1016/j.asoc.2017.11.007

[24] Zheng, S., Zhou, C., Jiang, X., Huang, J., & Xu, D. (2022). Progress on Infrared Imaging Technology in Animal Production: A Review. In Sensors (Vol. 22, Issue 3, p. 705). MDPI AG. https://doi.org/10.3390/s22030705

[25] Incropera, F. P., DeWitt, D. P., Bergman, T. L., & Lavine, A. S. (2007). Fundamentals of heat and mass transfer (Vol. 8, p. 116). New York: Wiley.

[26] Zheng, S., Zhou, C., Jiang, X., Huang, J., & Xu, D. (2022). Progress on Infrared Imaging Technology in Animal Production: A Review. In Sensors (Vol. 22, Issue 3, p. 705). MDPI AG. https://doi.org/10.3390/s22030705

[27] Eddy, A. L., Van Hoogmoed, L. M., & Snyder, J. R. (2001). The Role of Thermography in the Management of Equine Lameness. In The Veterinary Journal (Vol. 162, Issue 3, pp. 172–181). Elsevier BV. https://doi.org/10.1053/tvjl.2001.0618

[28] Creedon, N., Robinson, C., Kennedy, E., & Riordan, A. O. (2019). Agriculture 4.0: Development of Seriological on-Farm Immunosensor for Animal Health Applications. In 2019 IEEE SENSORS. https://doi.org/10.1109/sensors43011.2019.8956677

[29] Byrd, G. (2015). Tracking Cows Wirelessly. In Computer (Vol. 48, Issue 6, pp. 60–63). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/mc.2015.154

[30] Davison, C., Hamilton, A., Tachtatzis, C., Michie, C., & Andonovic, I. (2021). Keynote Speech 2: Data-driven Machine Learning Precision Livestock Farming Technologies and Applications. In 2021 Tenth International Conference on Intelligent Computing and Information Systems (ICICIS). 2021 Tenth International Conference on Intelligent Computing and Information Systems (ICICIS). IEEE. https://doi.org/10.1109/icicis52592.2021.9694131

[31] Abdulai, G., Sama, M., & Jackson, J. (2021). A preliminary study of the physiological and behavioral response of beef cattle to unmanned aerial vehicles (UAVs). In Applied Animal Behaviour Science (Vol. 241, p. 105355). https://doi.org/10.1016/j.applanim.2021.105355

[32] Ma, S., Yao, Q., Masuda, T., Higaki, S., Yoshioka, K., Arai, S., Takamatsu, S., & Itoh, T. (2021). Development of Noncontact Body Temperature Monitoring and Prediction System for Livestock Cattle. In IEEE Sensors Journal (Vol. 21, Issue 7, pp. 9367–9376). Institute of Electrical and Electronics Engineers (IEEE). https://doi.org/10.1109/jsen.2021.3056112

[33] Lovarelli, D., Tamburini, A., Mattachini, G., Zucali, M., Riva, E., Provolo, G., & Guarino, M. (2020). Relationships among behavior, climate and milk production in a dairy cattle farm in Northern Italy. In 2020 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor). https://doi.org/10.1109/metroagrifor50201.2020.9277654