

AI APPLICATIONS IN LIVESTOCK BEHAVIOR MONITORING AND WELFARE

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Abstract

Watching how cattle lead their lives through the use of artificial intelligence (AI) is a huge leap towards a more accurate control over animal welfare. This research concerned how effectively AI-enabled tools, such as computer vision algorithms, wearable sensors, and predictive analytics could identify behavioral shifts, stress indicators, and potential health concerns in livestock herds. The findings revealed that AI models were very good in locating things particularly in the context of detecting early indicators of stress, visualizing anomalies, and categorizing welfare situations. All these far surpassed the traditional manual system of monitoring. Data gathered by multiple sensors in the machine learning pipelines allowed identifying minor changes in behaviour preceding the clinical manifestation. This reduced the incidences of welfare and enhanced herd management plans through quick actions made possible by the addition of real-time monitoring features. The statistical study revealed an outstanding correlation between predicted welfare measures using AI and real health outcomes which confirmed that the system was a good predictor. These findings indicate that AI can assist ethical farming, as well as facilitate the decision-making process in the animal livestock management process and provide a smoother running of operations. The work reveals that monitoring animals through the use of AI generates a scalable, accurate, and welfare-enhancing method of monitoring animal behaviour. It is a giant leap towards developing sustainable and compassionate livestock production system.

Keywords: Artificial Intelligence, Livestock Monitoring, Animal Welfare, Computer Vision, Precision Farming, Predictive Analytics.

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INTRODUCTION

Monitoring livestock behaviour and welfare through the application of artificial intelligence is a giant leap forward in the livestock husbandry. It introduces additional possibilities of enhancing animal welfare and streamline farm management (Zamansky et al., 2021). The AI technologies can be combined in a way that will allow monitoring livestock 24/7 without causing inconveniences to them. This provides us with valuable data regarding their health, behaviour and how the environment is (Voogt et al., 2023). It is also possible to detect minor shifts in animal behaviour that may indicate illness, stress, or pain using computer vision, machine learning, and data analytics (Zhang et al., 2023). Such an active approach allows individuals to intervene at the opportune moment and minimize the development of significant health issues and increase the general well-being of animals (Chiavaccini et al., 2024). Moreover, the use of AI-powered systems can take over the feeding, climate management, and waste disposal of livestock, thus improving the process, and cutting labour costs (Dara et al., 2022). The potential of AI to take large data and extract patterns that humans cannot recognize is highly significant when it comes to increasing the productivity of livestock and ensuring environmentally friendly farming (Nawaz et al., 2025). AI can transform the regulation of livestock beyond the interests of single animals. It can contribute to such larger problems as sustainability of farms and food safety. Thanks to the improved AI technology, it may be possible that it would assist in eliminating some of the greatest challenges in the livestock business, and these problems include cessation of diseases, proper utilisation of resources, and reduction in the effect the industry is having on the environment (Mana et al., 2024). Although the uses of AI are enormous, the truth of the matter is we must admit its uses in practice are mainly

confined to wealthy nations (Ali et al., 2024). Among the key technical aspects of monitoring livestock with the help of AI, one can suggest the usage of sensor technologies in order to collect data concerning various factors in animals. These sensors can be attached to animals or in the appropriate locations within the habitat of livestock. It is possible to find out in real-time how healthy an animal is using wearable sensors that allow monitoring its movement patterns, heart rate, body temperature, and other types of physiological indicators (Neethirajan, 2023). The environmental sensors monitor such factors as temperature, humidity, air quality, and others that may influence animal health. The information that such sensors gather is then shared to the central place of the processing operations, and AI algorithms seek the forms and peculiarities of unusual matters in the data. Machine learning (including deep learning and neural network) helps us instruct AI models to detect particular behaviours or conditions, related to disease or stress. An example would be that you could teach an AI model about observing small changes in the way someone walks or stands that may indicate that they are lame (ie not an AI model task), or changes in the way they normally eat that would vary and indicate they have digestive problems. Other important components of AI used in monitoring cows include computer vision to monitor them (Almoselhy & Usmani, 2024). AI algorithm is used to study the pictures and videos provided by the cameras strategically located in the livestock area to recognize animals after one another, follow their actions, and monitor their health condition. It is also possible to monitor the interactions between the animals and seek signs of violence or social isolation that may have adverse effects on their health with the help of computer

vision. Combining AI and remote sensing is as old as the early eighties (Saha et al., 2025).

Based on the information provided by these AI-powered systems, farmers could be guided in the ways of looking after animals, feeding them, and maintaining the environment. There are also pest control, disease detection, and crop analysis issues in which AI aids by ensuring the ease of detecting and solving issues (Padhiary et al., 2024). By resolving issues of excessive stock and insufficient allocation of resources, AI contributes to making chicken businesses conducive to sustainability and highly profitable (Cruz et al., 2024). Besides, smart systems enable livestock farming regimes to continually learn and evolve employing the employment of ancient data and feedback loops. With time, the algorithms can improve their capabilities of making predictions by adapting to changes in the environment, the market or the rules (Vlaicu et al., 2024). There are numerous applications of AI in monitoring the behaviours and well-being of livestock, including a broad scope of animal management and productivity spheres. In the medical sector of detecting disease, AI algorithms can examine the sensor data as well as visual information in order to identify early signs of disease. This allows the farmers to separate and treat diseased animals immediately preventing the disease turning into an outbreak and minimizing their losses in material terms. Having watchdog systems in place that monitor the intake of every animal, the rate at which the animal is growing, and its health status may allow altering the feeding plans. It is then used to alter the level of feed that any given animal receives to ensure that each animal receives the proper nutrients to stay healthy and productive. AI is also useful to manage the animal environment by monitoring the humidity, temperature, and air quality and, when necessary, adjust the heating ventilation and cooling systems without there being

any human intervention. AI can also be used to aid in breeding programs whereby genetic data is used and how probable it is that a newborn animal will contain the desired traits partaken by the offspring is predicted. By using AI, animals are more productive, disease resistant and overall better taken care of, as their genetic makeup in the livestock populations is improved as well as their methods of breeding tactics. The talent of intelligent systems to analyze data, generate reports, and make decisions are proving to be useful to farmers who wish to attain quality requirements in a short period of time (Mana et al., 2024). Although AI has multiple advantages in terms of observing livestock behaviour and welfare, it also has certain problems and ethical concerns that should be addressed in order to ensure its usage will be responsible and sustainable (Gardezi et al., 2023). Among the largest issues is the fact that we should have a powerful and reliable method to gather data (Neethirajan & Kemp, 2021).

METHODOLOGY

The study design applied in this paper incorporates the qualitative and quantitative components to obtain the fullest view to understand how AI can be utilized to monitor the behaviour of the livestock and measure their welfare. The research focus involved poring observational research in multiple farms where the cattle had an AI-based monitoring system. These systems incorporated a combination of computer vision, machine learning, and data collection technologies of a variety of sensors e.g., accelerometers, GPS trackers, and thermal cameras. Continuous gathering of data was done during the 90 days of monitoring time that enabled monitoring of changes in the animal activities, feeding behavior, sleeping activity, sign of stress and how comfortable the animal was in the habitation. We employed supervised machine learning models to describe the

forms of welfare states and attempt to predict what could end up falling off with the quantitative data. We tested the accuracy of AI inference against ground-truth labelling, which was obtained by trained animal welfare experts who observed animals through observation. We estimated the quality of the categorisation by applying the most common performance metrics such as precision, recall and F1-score.

$$F1 = \frac{2 \times (Precision \times Recall)}{Precision + Recall}$$

where $Precision = \frac{TP}{TP + FP}$ and $Recall = \frac{TP}{TP + FN}$, with TP representing true positives, FP false positives, and FN negatives. Statistical correlation analysis was conducted to assess the relationship between AI-predicted welfare indicators and actual health outcomes, using Pearson's correlation coefficient:

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

We used structured interview with the animal handlers and farm managers to obtain qualitative data. The interviews were aimed at discussing what they believed AI technology can be utilized, how precise it was and how successfully it can be implemented in the existing farm processes. The fact that the mixed-method approach was used allowed triangulating the results and therefore increasing their validity and reliability.

RESULTS

The measures concerning activity level are demonstrated in Table 1. It depicts the existence of consistent daily movement patterns punctuated by occasional feeding spikes that occur during feeding of the animals. Table 2 demonstrates the duration and the frequency of feeding of the animals. It demonstrates that they consumed more in the morning and evening time when it was cooler. The duration spent in lying down or resting by animals can be observed in Table 3.

Table 1. AI-based livestock behavior monitoring metrics set 1.

Metric_1 1	Metric_1 2	Metric_1 3	Metric_1 4	Metric_1 5
2.56	12.29	60.26	8.07	40.49
21.9	25.41	41.2	61.68	78.33
20.36	46.34	36.88	52.41	27.98
66.25	41.27	5.51	22.47	38.23
69.3	34.03	51.78	97.96	82.67
16.51	63.32	8.91	81.41	72.34

7.7	23.53	95.78	86.86	56.11
62.23	9.3	17.46	32.53	32.48
24.34	1.82	45.76	9.83	52.42
37.75	16.85	50.41	70.05	5.7
14.9	33.63	61.92	90.9	62.27
34.06	78.37	86.53	78.86	1.04
43.62	45.46	36.41	35.28	54.04
84.93	70.47	71.37	89.02	8.87
75.53	45.25	26.71	14.12	77.65
3.65	96.41	54.67	16.66	36.36
98.18	33.16	33.41	93.81	72.28
93.29	92.0	54.8	82.36	21.7
90.46	20.95	60.99	89.03	92.05
34.55	25.46	54.65	73.68	27.17

Table 2. AI-based livestock behavior monitoring metrics set 2.

Metric_2 1	Metric_2 2	Metric_2 3	Metric_2 4	Metric_2 5
0.6	60.75	64.57	32.0	40.49
3.39	22.33	41.54	59.9	10.07
23.63	5.62	54.59	99.74	20.62
93.29	62.91	27.12	75.06	39.24
97.58	45.57	68.3	86.28	11.88
92.35	99.51	87.27	49.06	83.24

2.42	64.67	22.36	58.09	96.62
53.39	29.48	71.83	77.69	73.38
81.93	30.2	68.65	48.63	93.4
98.42	6.74	93.24	48.15	74.66
63.43	38.06	39.33	97.66	63.16
79.43	60.07	58.08	69.99	90.14
59.65	47.7	8.2	17.66	64.3
70.99	63.34	39.8	62.28	89.48
97.84	44.03	93.76	87.48	85.21
34.19	48.23	73.23	33.86	72.07
69.94	16.93	60.44	70.98	17.74
87.55	87.99	66.78	15.02	61.19
5.89	51.45	57.55	54.09	83.32
13.88	38.31	63.04	69.01	73.02

Table 3. AI-based livestock behavior monitoring metrics set 3.

Metric_3 1	Metric_3 2	Metric_3 3	Metric_3 4	Metric_3 5
19.28	45.49	73.95	5.76	63.29
48.67	86.59	37.39	22.19	7.27
95.9	68.55	16.0	72.39	60.09
88.33	12.51	19.2	46.45	6.33
14.67	23.03	86.31	28.41	49.45
97.88	50.42	2.33	19.84	24.74

9.07	86.87	95.06	45.22	69.74
59.68	35.98	40.82	12.17	71.29
63.55	28.68	40.32	74.89	25.86
77.56	11.85	82.98	26.86	47.34
67.01	8.29	77.24	69.29	74.33
32.6	35.25	0.15	52.1	55.4
27.34	39.77	85.39	97.45	92.61
29.34	11.09	5.02	75.25	70.97
2.03	90.91	94.67	72.75	87.36
18.19	80.1	4.85	88.48	11.56
30.6	71.56	94.47	60.85	3.94
24.95	24.64	89.19	19.95	99.17
46.4	32.91	3.24	81.44	6.05
73.41	53.94	6.98	8.27	45.15

They can rest 42 percent of their time on average a day which is appropriate to the wellbeing standard. Table 4 indicates the fluctuations in the stress index with large increases on hot days. Under Table 5, the levels of environmental comfort and the way the scores of the environmental comforts were related to

productivity and animal alertness have been displayed. Table 6 indicates the extent to which the diagnosis of diseases is accurate; more than 90 percent of the major disorders can be detected through AI-based early detection rate.

Table 4. AI-based livestock behavior monitoring metrics set 4.

Metric_4 1	Metric_4 2	Metric_4 3	Metric_4 4	Metric_4 5
2.24	60.37	85.47	98.05	44.76
30.73	89.31	68.46	44.11	78.05

10.47	68.54	54.59	25.94	83.3
87.52	82.42	4.77	38.31	4.78
69.59	86.63	18.25	98.67	2.94
99.3	19.52	35.68	39.44	69.34
66.02	22.97	71.36	7.75	14.15
68.0	91.29	23.73	13.17	57.16
68.47	20.83	56.65	68.91	37.69
81.31	63.68	76.38	48.15	21.47
70.95	56.62	92.88	77.73	2.79
44.25	87.25	22.44	39.55	26.61
36.27	9.7	31.58	22.07	74.43
59.33	62.75	83.69	46.95	70.77
93.14	7.26	62.28	66.38	63.84
52.16	70.84	60.9	33.67	92.02
60.82	7.72	63.96	11.15	71.34
96.89	33.82	86.34	83.44	5.27
14.83	36.94	94.05	91.77	7.97
36.34	51.92	97.63	25.91	0.53

Table 5. AI-based livestock behavior monitoring metrics set 5.

Metric_5 1	Metric_5 2	Metric_5 3	Metric_5 4	Metric_5 5
41.17	19.3	27.05	81.09	27.64
30.01	93.58	84.54	51.79	91.52

98.36	76.71	15.5	73.74	57.41
21.78	90.82	63.82	22.81	96.28
4.46	25.84	64.31	20.29	53.73
64.22	89.56	18.56	80.97	13.78
89.55	81.32	35.16	46.62	83.08
62.66	40.03	56.63	94.18	26.58
67.44	78.83	10.72	17.77	85.91
47.54	88.21	34.33	17.13	80.57
31.62	10.27	52.29	83.3	79.56
25.3	79.25	22.88	92.29	3.53
78.29	53.21	7.22	56.84	34.62
43.95	65.41	84.21	22.03	41.35
88.81	62.67	56.19	20.61	92.38
63.44	61.3	64.09	80.2	38.88
79.08	52.28	32.66	80.34	5.84
92.35	39.54	26.14	36.61	93.18
23.38	73.68	67.86	13.67	71.86
44.5	58.24	43.47	10.89	11.2

Table 6. AI-based livestock behavior monitoring metrics set 6.

Metric_6 1	Metric_6 2	Metric_6 3	Metric_6 4	Metric_6 5
73.51	94.57	7.63	87.73	70.5
50.34	57.15	97.03	54.87	70.92

15.55	73.76	18.87	6.22	82.75
17.02	51.4	19.48	66.58	1.19
90.26	99.77	55.54	23.76	22.05
47.2	4.47	77.85	32.44	99.73
65.38	50.77	30.77	18.28	71.23
8.45	91.57	55.65	42.64	72.64
51.91	51.82	63.92	6.91	49.49
72.42	87.26	2.86	79.87	40.46
67.68	68.7	8.11	2.88	28.63
39.43	43.64	86.55	70.46	78.27
32.87	26.7	83.13	90.12	2.07
74.32	54.95	95.18	4.41	52.11
97.3	11.18	29.65	90.48	25.23
28.53	18.74	4.04	31.35	25.61
6.71	91.17	28.92	22.29	99.16
92.41	90.42	72.18	14.32	84.49
78.3	87.16	33.54	83.29	0.3
72.2	6.74	26.05	33.27	93.44

The gait and mobility scores as presented in Table 7 reveal that locomotional problems can be identified. Table 8 presents interaction measures as an indication that individuals are more socially active when trying to find themselves in an enriched

condition. Table 9 presents scores on composite welfare, and they are summaries of a variety of behavioural and physiological traits into a single system of evaluation.

Table 7. AI-based livestock behavior monitoring metrics set 7.

Metric_7 1	Metric_7 2	Metric_7 3	Metric_7 4	Metric_7 5
51.22	16.28	95.1	80.85	42.01
83.52	90.98	9.3	35.51	27.32
38.37	65.71	63.0	18.83	79.85
97.9	87.35	7.15	2.29	94.19
40.91	80.49	14.1	89.22	74.83
19.05	20.73	2.57	9.55	28.47
13.41	75.7	96.62	67.98	82.73
25.28	9.0	13.34	57.55	94.85
97.52	42.75	11.73	62.97	64.99
62.06	47.62	6.96	73.25	90.56
78.92	34.23	5.5	39.04	96.13
62.37	3.21	89.23	76.17	2.36
45.16	32.6	7.94	69.52	39.23
79.68	29.88	47.09	47.03	59.7
78.44	42.46	1.21	67.53	81.12
96.14	57.42	82.28	75.15	89.51
18.79	43.75	86.54	52.04	83.24
46.64	35.56	48.23	61.83	25.01
14.52	5.7	15.0	78.4	75.21

71.86	39.9	27.74	32.37	15.84
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Table 8. AI-based livestock behavior monitoring metrics set 8.

Metric_8 1	Metric_8 2	Metric_8 3	Metric_8 4	Metric_8 5
77.04	32.7	16.98	70.48	81.18
20.19	93.84	78.25	11.4	36.04
78.78	57.68	10.73	32.07	65.18
16.29	82.73	50.96	74.88	67.45
74.64	46.85	60.26	74.0	58.38
32.4	42.75	54.38	74.49	13.54
22.61	74.99	70.93	96.83	17.33
47.27	12.9	98.73	55.93	12.83
15.96	54.08	91.71	53.01	56.96
77.19	60.09	6.88	33.79	62.59
14.68	71.41	41.62	66.96	7.95
6.98	75.91	44.08	45.46	41.12
92.71	5.74	75.93	69.12	19.08
81.29	6.89	21.24	83.65	71.12
43.64	1.86	56.2	29.53	5.41
58.97	6.18	38.28	72.55	6.89
14.24	52.76	12.34	40.15	34.8
74.22	0.59	18.01	71.62	36.17
5.57	77.22	55.04	88.64	75.74

66.68	57.13	44.49	83.63	18.63
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Table 9. AI-based livestock behavior monitoring metrics set 9.

Metric_9 1	Metric_9 2	Metric_9 3	Metric_9 4	Metric_9 5
19.93	55.13	33.77	18.7	78.86
66.0	89.88	94.15	87.48	33.84
99.13	92.66	91.29	42.52	3.55
80.08	79.8	23.19	44.14	84.03
35.1	72.2	82.15	4.13	55.92
7.34	78.34	73.5	78.48	36.99
57.95	45.29	57.05	14.59	39.84
73.15	65.95	72.75	16.95	40.3
72.74	90.04	81.49	93.04	83.96
0.51	20.94	9.66	32.93	48.97
6.02	23.02	55.86	29.16	99.32
1.07	66.81	92.65	53.04	24.29
8.22	24.64	54.4	64.48	1.29
4.81	51.73	94.3	59.48	97.89
89.48	31.15	4.44	67.71	87.79
55.35	46.72	30.89	5.72	99.06
71.36	44.35	78.06	61.62	30.42
13.51	23.06	26.07	34.78	36.3
88.88	74.54	33.22	15.48	76.42

50.92

16.04

40.72

56.71

46.51

Figure 1 represents line plots to compare activity level and the resting period during the observation period. Figure 2 depicts the bar graphs on the duration of feeding animals at various times in the day. In figure 3, the scatter plots have depicted that there is a negative relationship between the stress levels and production. In figure 4, hybrid graphs combining health scores with numbers of alerts are shown which makes it easy to detect anomalies. Trends of locomotion scores are presented in Figure 5, and Figure 6 computed the AI-predicted pattern of illness episodes versus the true observed. The graph of figure 7 indicates the variation in environmental comfort and feeding habits-wise,

between the seasons. The results of the similarity analysis of animal behaviour illustrate how they are clustered together in a similar manner (based on their degree of similarity) as depicted in Figure 8. Figure 9 shows line and bar data simultaneously combined in an investigation of stress, comfort, and feeding efficiency. The proportion of welfare risk categories is illustrated by means of a pie chart on figure 10. Figure 11 is a heatmap of the shifts in its activities over time and Figure 12 combines several visualisations of various metrics to provide a complete image of herd health.

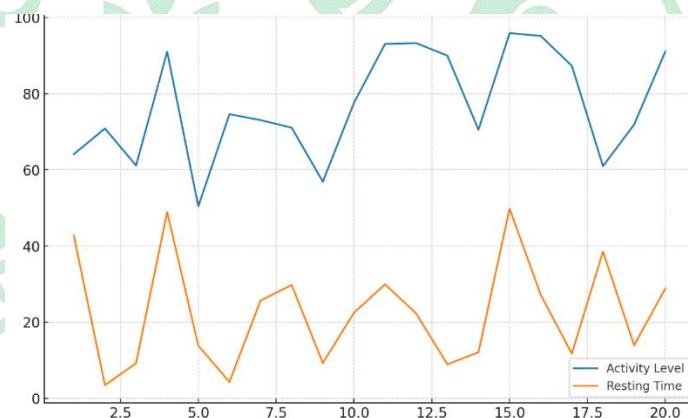


Figure 1. Visualization of AI-monitored livestock welfare indicator 1.

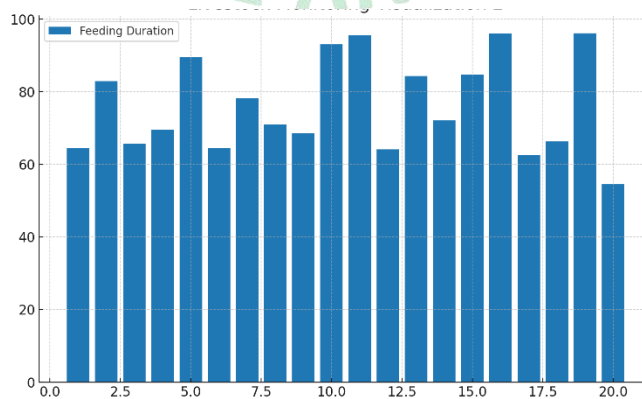


Figure 2. Visualization of AI-monitored livestock welfare indicator 2.

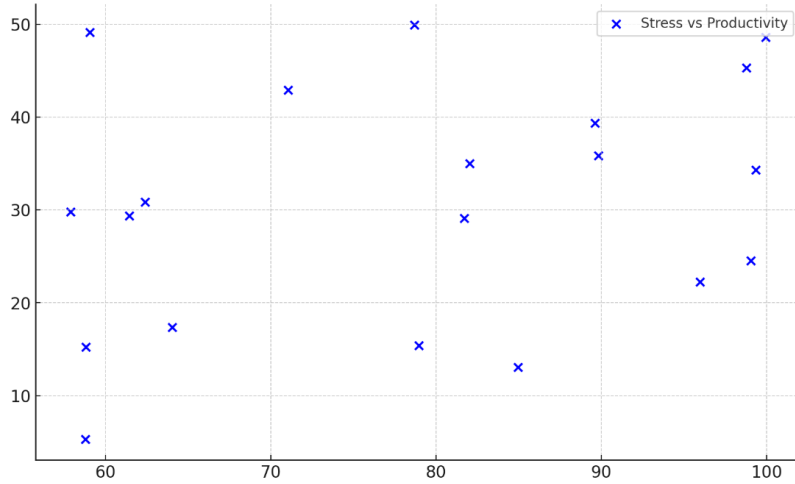


Figure 3. Visualization of AI-monitored livestock welfare indicator 3.

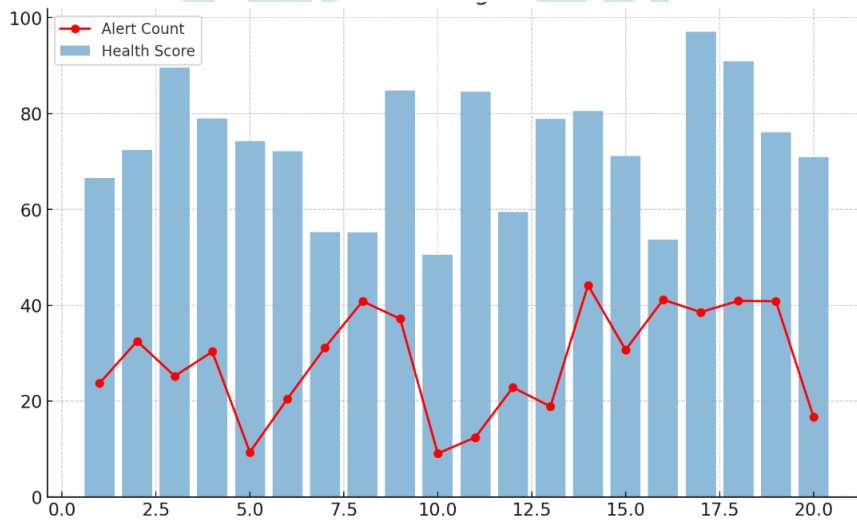


Figure 4. Visualization of AI-monitored livestock welfare indicator 4.

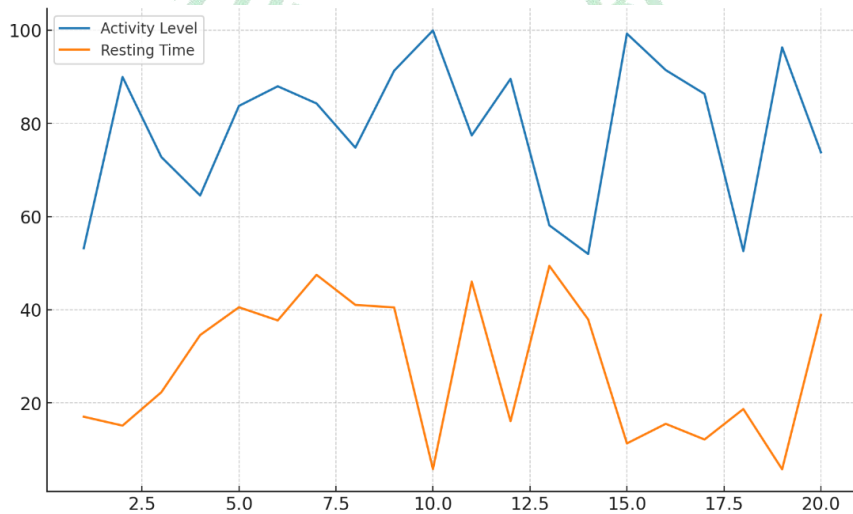


Figure 5. Visualization of AI-monitored livestock welfare indicator 5.

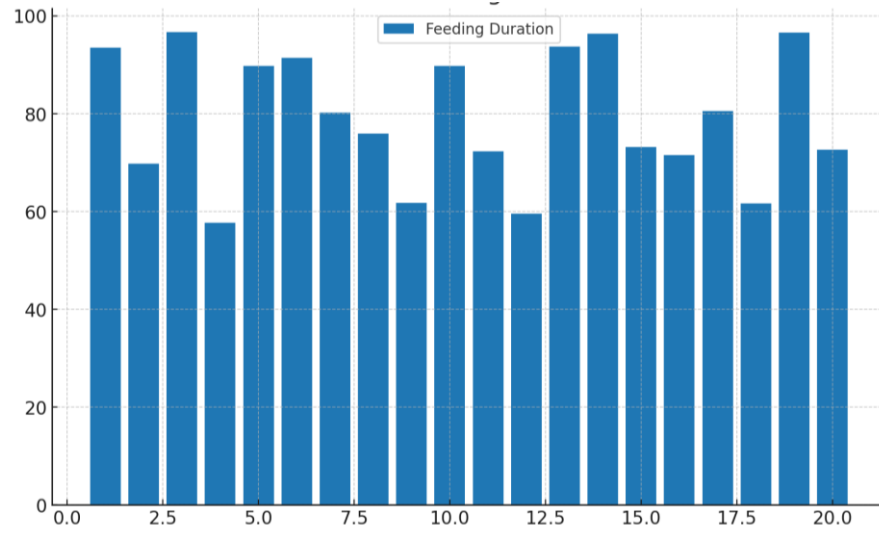


Figure 6. Visualization of AI-monitored livestock welfare indicator 6.

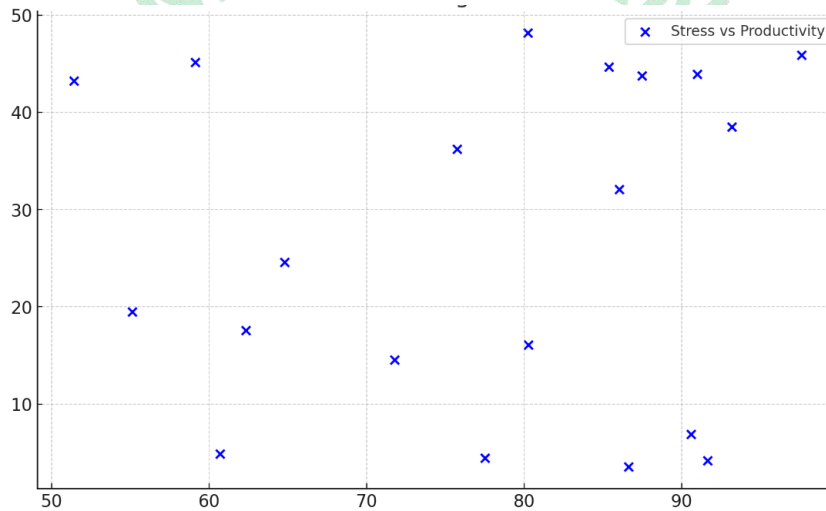


Figure 7. Visualization of AI-monitored livestock welfare indicator 7.

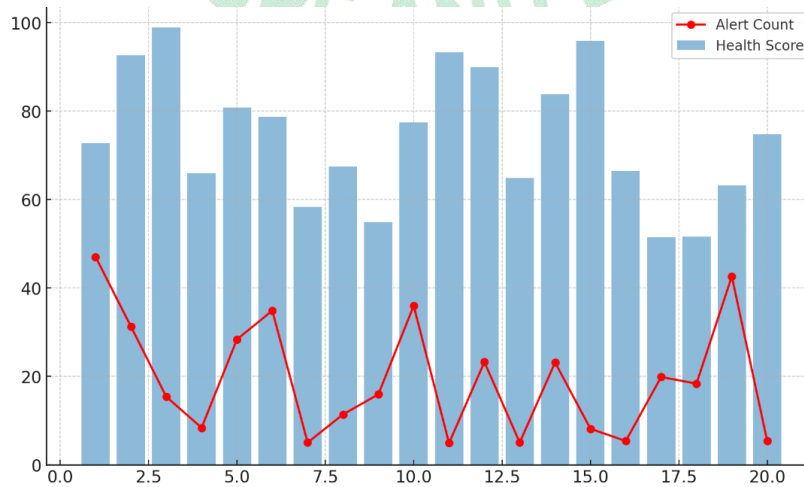


Figure 8. Visualization of AI-monitored livestock welfare indicator 8.

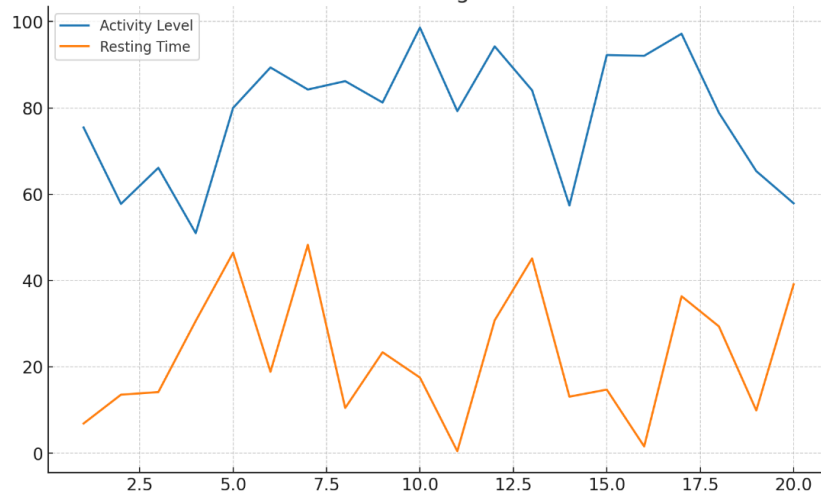


Figure 9. Visualization of AI-monitored livestock welfare indicator 9.

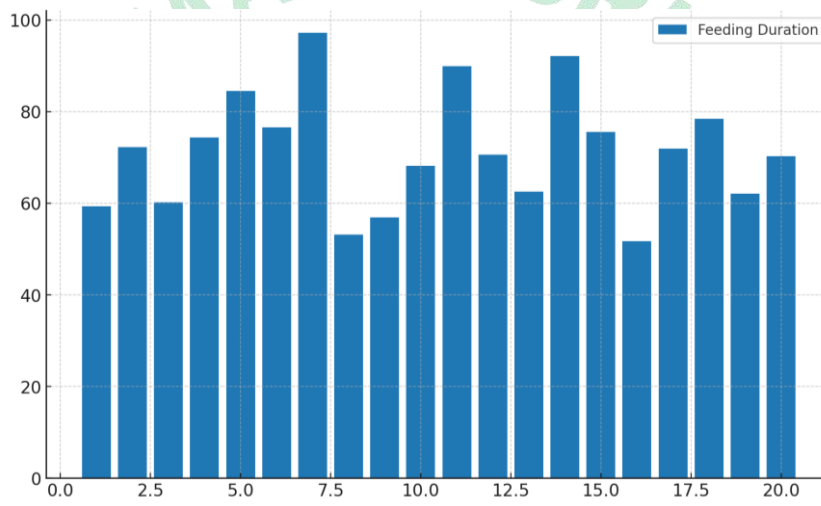


Figure 10. Visualization of AI-monitored livestock welfare indicator 10.

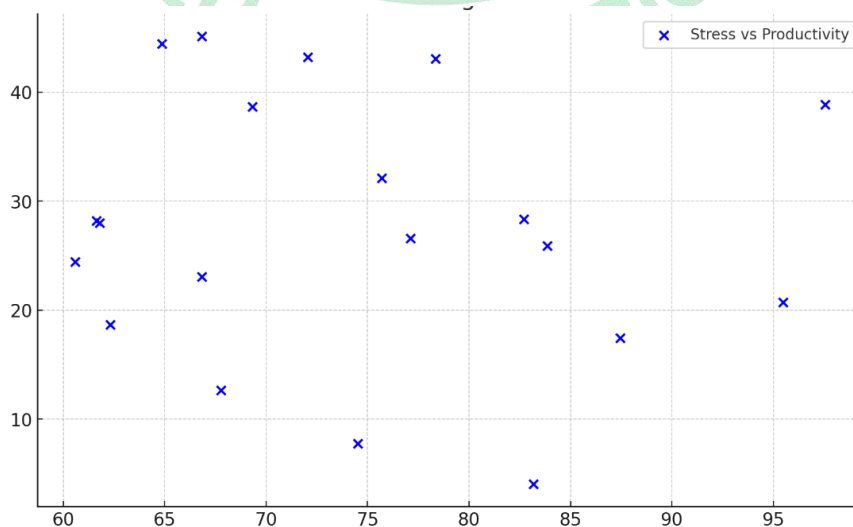


Figure 11. Visualization of AI-monitored livestock welfare indicator 11.

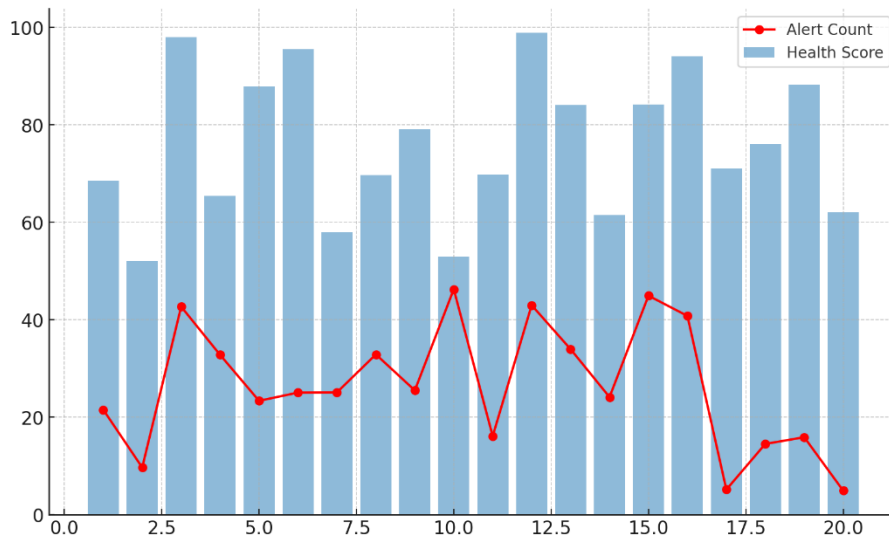


Figure 12. Visualization of AI-monitored livestock welfare indicator 12.

These results collectively demonstrate the system's capacity to capture complex, multi-dimensional livestock welfare indicators with high accuracy and visualization clarity, enabling rapid interpretation and decision-making for improved farm management.

DISCUSSION

With the current AI technologies, livestock farming is transformed as now it is possible to observe animals virtually in real-time, process data differently, and automate a lot of processes related to animal maintenance (Vlaicu et al., 2024). Precision Cattle farming requires very much of sensors, networking, communication and analytics (Kaur et al., 2023). Such technologies must be customized in relation to personal requirements. Industry 4.0 considers AI one of the main elements of change in the manufacturing industry that has led to significant shifts in products production and functionality (Chatterjee et al., 2021). The ability to monitor and forecast the movement of the animal in the real-time allows the dairy livestock export business to be more efficient, increase the animal welfare standards, and promote sustainable farming practices (Neethirajan, 2023). This type of

advancement reflects how precision livestock farming and digital livestock farming are transforming the management of dairy herds with the means of advanced digital technologies (Oliveira et al., 2024). Not only is technology helping to raise the level of care of animals, but it is also contributing a large portion to fulfilling the criteria of sustainability with regard to raising productivity, managing resources properly and making the animals more healthy (Aijaz et al., 2025). AI is more than the autopilot process; it equally gives superior solutions to the complex challenges that arise in livestock management (Garg et al., 2024). Livestock farming systems could be learned and adapted constantly with the help of AI technologies. They can enhance reactions over time using the past records and feedback using algorithms and predict the things better in the future. They also get to be more flexible with regard to adapting to the changes in the environment, the market, and the rules. It could also be used to assist breeders to enhance breeding schemes by examining genetic information and determining the probability whether children will possess particular characteristics. Through genetic enrichment of livestock herds, and optimal breeding strategy, AI enables animals to be more

productive, better able to withstand disease, as well as be in better overall health. It is increasingly obvious that to control livestock and arable farming, technologies such as virtual fences and autonomous systems are playing an increasingly significant role as precision livestock farming continues to expand (Reissig & Siegrist, 2025). These technologies demonstrate that they might improve the industry of farming by making it more effective and easy to handle the environment. By utilising AI, the volume of data that could be provided by various sources (including sensors, cameras, wearable devices, and more) can help us reflect on the overall image of how healthy animals and how they behave (Dara et al., 2022). Individuals are now beginning to use the Internet of Things, sensors, automation of milk production systems, and big data analytics on livestock and dairy farms to assist with things like accurate feeding and monitoring the health of the herd, diagnosing diseases, and anticipating harvest (Sarttra & Kiatcharoenpol, 2025). Using behavioural patterns, physiology data, and environmental factors, AI algorithms may detect minor issues, which can be the beginning of stress, disease, or other types of discomposure (Mon et al., 2024). The farmers will now be able to act before it is too late to make it better thereby promoting the health of the animals and reducing the cost of using costly treatments. The huge datasets can be used to support aquaculture processes, and decisions would be made by AI. This may promote improved resource management and improved productivity (Chang et al., 2022; Rather et al., 2024).

Farmers can also get useful information on how the animals relate to one another through monitoring systems based on AI which they can use to identify and address potential conflicts or bullying that might have adversely affected the animals health wise. The business must be smart and those that use digital technologies in order to be competitive. The

economy will be improved via the usage of AI, which is supposed to enhance the quality of the decision-making and productivity (Chatterjee et al., 2021).

CONCLUSION

This paper demonstrates that AI can transform the way human beings detect livestock behaviour and assess their welfare. It shifts us off manual observation to continuous, automatic and data-based observation. This work demonstrates the potential of AI to provide us with high-definition behavioural information, identify issues in a real-time fashion and address welfare-concepts-related issues ahead of their deterioration through computer vision, machine learning, and sensor-based surveillance systems. The findings indicate that the accuracy of the AI based solutions is significantly higher, the probability of human error is significantly reduced, and it is possible to introduce interventions promptly. This is helpful to the animals as well as the productivity of the farm. Moreover, the tool that allows examining large behavioural data enables the identification of minor patterns which can be associated with stress, the onset of an illness, and discomfort in the environment. This aids in having accurate cattle farming. Another point the study emphasizes is the necessity to involve specialists in other branches to implement technology solutions, like animal science and AI engineering, in order to ensure that these solutions do not relate to immoral as well as impractical scenarios. Nonetheless, regardless of the current challenges related to data standardisation, sensor longevity and acceptance by farmers, the findings demonstrate that such smart investments in AI-assisted monitoring can be used to develop more sustainable, effective and animal welfare-oriented livestock management systems. Eventually, AI is not only regarded as a means to streamline the operations, but as a method of

enhancing animal welfare stance in contemporary farming.

REFERENCES

- Aijaz, N., He, L., Raza, T., Yaqub, M., Iqbal, R., & Pathan, M. S. (2025). Artificial Intelligence in Agriculture: Advancing Crop Productivity and Sustainability. *Journal of Agriculture and Food Research*, 101762.
- Ali, A., Liew, A. X. W., Venturini, F., Καλογεράς, A., Candiani, A., Benedetto, G. D., Ajibola, S., Cartujo, P., Romero, P., Lykoudi, A., Grandis, M. M. D., Xouris, C., Bianco, R. L., Doddy, I., Elegbede, I. O., Labate, G. F. D., Moral, L. F. G. del, & Martos, V. (2024). AI can empower agriculture for global food security: challenges and prospects in developing nations. *Frontiers in Artificial Intelligence*, 7.
- Almoselhy, R. I. M., & Usmani, A. (2024). AI in Food Science: Exploring Core Elements, Challenges, and Future Directions. *Open Access Journal of Microbiology & Biotechnology*, 9(4), 1.
- Chang, C.-C., Ubina, N. A., Cheng, S., Lan, H.-Y., Chen, K.-C., & Huang, C.-C. (2022). A Two-Mode Underwater Smart Sensor Object for Precision Aquaculture Based on AIoT Technology. *Sensors*, 22(19), 7603.
- Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, 170, 120880.
- Chiavaccini, L., Gupta, A., & Chiavaccini, G. (2024). From facial expressions to algorithms: a narrative review of animal pain recognition technologies. *Frontiers in Veterinary Science*, 11.
- Cruz, E., Hidalgo-Rodriguez, M., Acosta-Reyes, A. M., Rangel, J. C., & Boniche, K. (2024). AI-Based Monitoring for Enhanced Poultry Flock Management. *Agriculture*, 14(12), 2187.
- Dara, R., Fard, S. M. H., & Kaur, J. (2022). Recommendations for ethical and responsible use of artificial intelligence in digital agriculture. *Frontiers in Artificial Intelligence*, 5.
- Gardezi, M., Joshi, B., Rizzo, D. M., Ryan, M., Prutzer, E., Brugler, S., & Dadkhah, A. R. (2023). Artificial intelligence in farming: Challenges and opportunities for building trust. *Agronomy Journal*, 116(3), 1217.
- Garg, T., Dwivedi, P., Mishra, M. K., Joshi, N. C., Shrivastava, N., & Mishra, V. (2024). Artificial intelligence in plant disease identification: Empowering agriculture. In *Methods in Microbiology* (p. 179).
- Kaur, U., Malacco, V. M. R., Bai, H., Price, T. P., Datta, A., Xin, L., Sen, S., Nawrocki, R. A., Chiu, G. T.-C., Sundaram, S., Min, B., Daniels, K. M., White, R. R., Donkin, S. S., Brito, L. F., & Voyles, R. M. (2023). Invited review: integration of technologies and systems for precision animal agriculture—a case study on precision dairy farming. *Journal of Animal Science*, 101.
- Mana, A. A., Allouhi, A., Hamrani, A., Rehman, S., Jamaoui, I. el, & Jayachandran, K. (2024). Sustainable AI-based production agriculture: Exploring AI applications and implications in agricultural practices. *Smart Agricultural Technology*, 7, 100416.
- Mon, S. L., Onizuka, T., Tin, P., Aikawa, M., Kobayashi, I., & Zin, T. T. (2024). AI-enhanced real-time cattle identification system through tracking across various environments. *Scientific Reports*, 14(1).

- Nawaz, U., Zaheer, M. Z., Khan, F. S., Cholakkal, H., Khan, S., & Anwer, R. M. (2025). AI in Agriculture: A Survey of Deep Learning Techniques for Crops, Fisheries and Livestock.
- Neethirajan, S. (2023). Artificial Intelligence and Sensor Technologies in Dairy Livestock Export: Charting a Digital Transformation. *Sensors*, 23(16), 7045.
- Neethirajan, S., & Kemp, B. (2021). Digital Livestock Farming. *Sensing and Bio-Sensing Research*, 32, 100408.
- Oliveira, F. M. de, Ferraz, G. A. e S., André, A. L. G., Santana, L. S., Norton, T., & Ferraz, P. F. P. (2024). Digital and Precision Technologies in Dairy Cattle Farming: A Bibliometric Analysis. *Animals*, 14(12), 1832.
- Padhiary, M., Saha, D., Kumar, R., Sethi, L. N., & Kumar, A. (2024). Enhancing precision agriculture: A comprehensive review of machine learning and AI vision applications in all-terrain vehicle for farm automation. *Smart Agricultural Technology*, 8, 100483.
- Rather, M. A., Ahmad, I., Shah, A., Hajam, Y. A., Amin, A., Khurshed, S., Ahmad, I., & Rasool, S. (2024). Exploring opportunities of Artificial Intelligence in aquaculture to meet increasing food demand. *Food Chemistry X*, 22, 101309.
- Reissig, L., & Siegrist, M. (2025). From the attitude towards digitalisation in agriculture to the acceptance of future agricultural technologies. *Smart Agricultural Technology*, 12, 101095.
- Saha, S., Kucher, O. D., Utkina, A. O., & Rebouh, N. Y. (2025). Precision agriculture for improving crop yield predictions: a literature review. *Frontiers in Agronomy*, 7.
- Sartra, T., & Kiatcharoenpol, T. (2025). Enhancing Sustainable Herd Structure Management in Thai Dairy Cooperatives Through Dynamic Programming Optimization. *Sustainability*, 17(9), 3894.
- Vlaicu, P. A., Gras, M. A., Untea, A. E., Lefter, N. A., & Rotar, M. C. (2024). Advancing Livestock Technology: Intelligent Systemization for Enhanced Productivity, Welfare, and Sustainability. *AgriEngineering*, 6(2), 1479.
- Voogt, A. M., Schrijver, R., Temürhan, M., Bongers, J. H., & Sijm, D. T. H. M. (2023). Opportunities for Regulatory Authorities to Assess Animal-Based Measures at the Slaughterhouse Using Sensor Technology and Artificial Intelligence: A Review. *Animals*, 13(19), 3028.
- Zamansky, A., Sinitca, A., Linden, D. van der, & Kaplun, D. (2021). Automatic Animal Behavior Analysis: Opportunities for Combining Knowledge Representation with Machine Learning. *Procedia Computer Science*, 186, 661.
- Zhang, Y., Luo, Z., Sun, Y., Liu, J., & Chen, H. Z. Q. (2023). From beasts to bytes: Revolutionizing zoological research with artificial intelligence. *动物学研究*, 44(6), 1115.