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INFRARED THERMOGRAPHY AND MACHINE LEARNING IN LIVESTOCK PRODUCTION

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ABSTRACT

This review presents infrared thermography, its application in livestock production and its integration with machine learning algorithm to provide an end-to-end solution towards enhancedproductivity. Infrared thermography is a simple non-contact, non-invasive method to detect surface temperature radiated from an animal skin. Temperature data is used to generate images called thermograms which can be used for diagnosis of diseased and non-diseased conditions. Real time collection of thermal data has resulted in huge volume of data, which requires the use of machine learning algorithms to assist the farmers gain insights that could be used to make informed decisions. The potential of the integration of machine learning and infrared thermography in livestock production have been explored. The areas of application include identification of unique features of individual animals, real time tracking of animals and determining breathing patterns that could indicate stress and pain. With improved understanding of how machine learning algorithms can be integrated with infrared thermography, farmers can explore other areas of application of both infrared thermography and machine learning to improve health, welfare and productivity of livestock.

Keywords: Infrared thermography; machine learning; infrared; livestock production; thermogram

1.0 INTRODUCTION

Infrared thermography (IRT) is a simple non-contact, non-invasive method of detecting heat emitted as infrared radiation by a surface. Infrared radiation is part of electromagnetic spectrum that is not visible to human eye but felt as heat. Objects with temperature above absolute zero (0^oK or 273^oC) radiate infrared radiation as waves proportionate to their body temperature, thus, the higher the temperature of an object the greater infrared radiation that will be emitted. Thermal camera captures infrared radiation from target animals and their background. The temperature data is represented in pictorial forms called thermograms. Temperature distribution within a thermogram can be used to determine the condition of an animal and is often analyzed manually using proprietary software. This requires the user to identify and select specific regions of the image called regions of interest (ROIs) for further analysis. Manual selection of the ROIs, especially in large thermographic datasets, is time consuming, labour intensive and subjective as it relies on user experience which may not provide timely information required for proactive decision making in critical conditions. Thus, automatic analysis of thermograms is desirable.

IRT was developed in the 1960s in the United States primarily for military surveillance and heat signature detection (Rogalski, 2012). In recent years, it has enjoyed widespread non-military application in numerous fields including engineering structural assessment (Abdelhamid and Sougrati, 2021), medical imaging and diagnosing (Goncalves et al., 2019) as well as ecological applications (Karp, 2020, Schneider et al., 2020). In veterinary medicine, the technology was largely adopted based on its ability to measure changes in animal surface temperature which may be associated with underlying physiological (Nahm, 2013; Jansson et al., 2021), metabolic (Ferreira et al., 2011) and behavioural processes and mechanisms (Perez Marquez, et al., 2019; Ferreira et al., 2020; Franchi et al., 2021). Detecting changes in surface temperature of animals by IRT has been used to identify onset of fever often associated with inflammation and diseases. IRT has been used to detect diseased conditions in animals including bovine viral diarrhea (BVD) (Schaefer et al., 2004), lameness in cattle (Abuelo et al., 2016; García-Munoz et al., 2017), foot and mouth disease in cattle (Gloster et al., 2011) and sheep (Rainwater-Lovett et al., 2009), early detection of blue tongue viral disease in sheep (Perez de Diego et al., 2013), mastitis in dairy cattle (Martins et al., 2013), foot lesions in sheep (Talukder et al., 2014), identify sick or stressed pigs (Siewert et al., 2014) and heat stress in poultry (Edgar et al., 2013, Abudabos et al., 2013). IRT can also be used to detect non-diseased conditions including pregnancy and reproduction (Barros de Freitas et al., 2018, Vicentini et al., 2020) and animal welfare and production (Montanholi et al., 2008; Nascimento et al., 2014).

In modern livestock agriculture, there is increase in intensive production system to meet global demand for animal protein. This method of raising animals has led to increased herd sizes resulting in inadequate monitoring of farm animals to assess health and welfare. To ensure adequate monitoring of animals, there is need to adopt modern technologies including IRT for remote real time monitoring. This technology however generates huge amount of data. Automatic analysis of large thermographic datasets is desirable to provide information to support decision making and enhance proactive measures. Many animal husbandry decisions are made easier through automated livestock farming systems for early warnings and intervention (Lowe et al., 2019). This has led to reduction of unnecessary medical treatments and labour and treatment costs resulting in higher profit margins. Automated systems requires the use of intelligent computer systems which employs machine learning algorithms to learn large datasets and produce outcomes that can assist the farmers to improve productivity. Machine learning algorithms can be applied to thermographic data to identify ROIs and can further process temperature data in selected ROIs to predict outcomes (Kim and Hidaka, 2021).

In this review, I will describe the principles of infrared thermography and review current knowledge on its application in livestock production. Also, the fundamentals of machine learning will be examined and recent studies on its integration with infrared thermography to improve livestock productivity will be reviewed.

2.0 BASIC PRINCIPLES OF INFRARED THERMOGRAPHY

IRT measures the radiation emitted by a surface in the infrared range of the electromagnetic spectrum. Electromagnetic radiation (EMR) is energy that is transmitted as both electrical and magnetic waves. The wavelength of the visible part of the EMR is in the range of 400 – 700nm and is often called the light spectrum. Infrared radiation is a part of the EMR with shorter wavelength typically between 750nm and 1mm. It is not visible to the human eye but can be felt as heat. The infrared radiation emitted by an object is proportional to its temperature; as objects get hotter, they emit more energy. The energy is dissipated from the surface of the animal through the skin as heat and can be measured using an infrared camera.

The measurement of temperature emitted from the surface of an animal's skin is affected by several factors including emissivity and reflectivity. Emissivity is the ability of an object to radiate infrared energy and is affected by the temperature of the surface, wavelength and angle of radiation. The surface temperature of an object determines the wavelength of the emitted temperature. A body with higher temperature emits energy at shorter wavelength. The emissivity of an object is compared to the emissivity of a standard body – the black body. A black body is called a perfect emitter as it is able to emit infrared radiation at all wavelengths and as such is given an emissivity value of 1.0. It is impossible for an object to achieve perfect emissivity as part of the energy radiated is reflected back inside the object and not released by radiative means; therefore the emissivity value is less than 1.0. The emissivity of biological materials ranges between 0.95 and 0.98 (Speakman, 1998) which may be attributed to the high water content present within it. Electromagnetic waves travel in straight lines. Thus, to receive the full intensity of the radiation, the angle of view between the thermal camera and the object is important. If the angle of view is small, the intensity of the infrared emission is reduced and it makes the object appear cooler than it is. Emissivity of animal skin is affected by different factors including the amount of hair or plumage coverage on the skin surface being measured, dirt or foreign materials andthe presence or absence of moisture which impacts the amount of heat lost to the environment (Zhao et al., 2013). It is important to understand the emissivity of the measuring surface and make corrections on thermal images to achieve accurate and reliable temperature measurements.

Reflectivity is another factor that influences accurate measurement of infrared emission. It is a critical element to consider when taking images of objects with low emissivity. Reflectivity is the measure of radiation reflected from the surface of an object, including objects in the background, the sky and the operator of the camera. These reflected radiations may bounce off the subject and strike the sensors in the thermal camera which may skew the accuracy of the thermal image being measured. Thus, for increased accuracy, measurement should be taken out of direct sunlight and wind drafts.

Other factors for accurate measurement by the thermal camera include camera focus, temperature range and operating distance. During measurement, the object must be kept in focus of the thermal camera to ensure accurate detection of heat emitted from the object. It is essential for thermal camera to detect values within the temperature range emitted by the object to prevent loss of data due to out-of-range values. Distance has direct effect on conduction of heat energy. Heat loss increases with distance travelled. Operating distance is the distance the IRT camera is placed from the object during measurements. Since heat flows from hot to cold regions, the distance it travels between the object measured and the thermal camera is also important. To ensure that the thermal camera is able to detect most of the heat conducted by the object and to reduce the amount of heat lost to the environment, the operating distance must be kept as short as possible. Thus, a controlled environment or standardized operating procedure is important to ensure the reliability of thermography imaging.

Healthy animals have balanced temperature distribution in different parts of the body. However, different anatomical regions including thigh, feet flank, muzzle, ear, eye, rump, udder, shoulder have different temperature and emit varied amount of heat (Montanholiet al., 2008; Soerensenet al., 2014; Soerensen and Pederson, 2015). The variation in temperature has been measured by IRT for assessment of stress conditions and other physiological parameters (Mantanholiet al., 2008; Soerensenet al., 2014; Weschenfelderet al., 2014; Soerensen and Pederson, 2015).

3.0 APPLICATION OF INFRARED THERMOGRAPHY IN LIVESTOCK PRODUCTION

Health of production animal is crucial for increased productivity and improved economic returns. Body temperature is an important physiological indicator to determine the health status of livestock as it is directly related to the health, reproductive success and productivity of farm animals (Koltes et al., 2018). Metabolic and physiological health status of animals involves the use of conventional invasive methods that requires contact between the animal and the temperature reading device. This requires the animal be captured and restrained for clinical examination, a labour intensive process and the results obtained from such invasive methods are often inaccurate and unreliable (Soerensen and Pederson, 2015). The process of handling and restraining may increase the stress level of the animal (Stewart et al., 2010; Magnaniet al., 2011) and could increase the risk of spread of diseases within livestock population attributed to the contact measuring device and frequent handling. Thus, the application of a non-invasive, non-contact measuring tool is desirable.

Animal surfaces radiate heat which can be absorbed by other bodies around them (Roberto et al., 2014). When animals experience stress, it alters their body temperature and influence blood flow and heat loss from the animal (Schaefer et al., 2002). Diseases conditions increase the body temperature of an animal which is dissipated as infrared energy to the environment. The heat radiated from the surface of an animal can be measured using IRT and the radiation translated into a pictorial representation of the distribution of surface temperature (Soroko and Zaborski, 2020). The picture provides both qualitative and quantitative information about the surface temperature of targeted tissues (Soroko and Howell, 2018).

IRT has widespread adoption in livestock farming to improve health, welfare and productivity of animal. It is a non-invasive method to reduce stress, increase cost effectiveness and allow for early identification of detrimental conditions for effective application of preventive and treatment measures.

3.1 LAMENESS

Lameness is a serious issue in large animals and poultry affecting performance, welfare and significant economic implications. Incidences of lameness are associated with disease, age, genetics, management practices, nutritional deficiencies, humidity and hygiene (Keyserlingk et al., 2009; Cook et al., 2012; Abuelo et al., 2016). Reduction in occurrence of lameness requires early recognition to initiate immediate treatment as a preventive measure (García-Munoz et al., 2017). In dairy animal, lameness is usually diagnosed by hoof trimming based on visual assessment (Alsaaod et al., 2015; Rodriguez et al., 2015). The traditional methods are cheap, time-consuming, non-invasive and ineffective (Schlagater-Tello et al., 2014). IRT has been used to detect abnormalities by measuring skin surface temperature. IRT as a diagnostic method for hoof disease uses alteration in skin surface temperature in response to inflammation (Alsaaod and Büscher, 2012).

In broiler chickens, lameness is a major welfare issue that causes considerable pain. Lame birds suffered from insufficient nutrient attributed to limited movement resulting in decreased growth and performance. Economic returns on farms are influenced by removal of affected birds. Bacterial chondronecrosis with osteomyelitis is a bacterial infection of the limbs in poultry. It is one of the leading causes of lameness in chickens globally with huge economic effect in fast-growing flocks. Weimer et al. (2019) measured surface temperature of broiler leg using IRT was compared to the severity of bacteria chondronecrosis with osteomyelitis lesion in healthy and lame birds. Subclinical lesion attributed to bacteria chondronecrosis with osteomyelitis characterized by increased leg temperature was detected by IRT. They concluded that application of the tool can reduce incidence of bacteria chondronecrosis with osteomyelitis induced lameness in broilers (Weimer et al., 2019). Weimer at al. (2020) studied stress by determining eye and the beak thermal surface temperature in clinically healthy broiler chicken using IRT. Lame birds demonstrate lower surface temperature of eye and beak. They concluded that surface temperature of the beak more than the eye provides a noninvasive indicator of stress in broilers.

In healthy animals, hoof temperature is generally lower compared to hoof with lesion (Bobic et al., 2017) this makes it suitable to use IRT as a tool for early detection before the onset of clinical signs. In the study by Gianesella et al. (2018) dairy cows were assessed for foot lesions using IRT.Cows having infected foot showed higher temperature than healthy ones. The authors concluded that IRT in dairy cows is a potential reliable tool for hoof lesion assessment. A similar study was conducted by LokeshBabu et al., 2018. The authors determined the onset of lameness by measuring changes in the coronary band and hoof skin surface temperature. They concluded that IRT is a possible diagnostic tool to monitor hoof surface temperature and useful for general routine assessment of hoof health (LokeshBabu et al., 2018). Bryne et al. (2019) conducted their study on detecting lameness in sheep. Their findings showed that large differences exist between temperature of healthy and infected hooves. It was suggested that lameness in sheep could be sensed using IRT and assessed at low temperature.

3.2 INFLAMMATION AND DISEASES

Diseases exert direct devastating impact on livestock productivity (decreased performance, morbidity and mortality) and indirect (limit preventive and control measures).Diseases are often diagnosed at onset of symptoms, when treatments are often less effective to result in significant economic loss. Thus, early detection and identification of diseases is crucial for effective disease management.

Inflammation is a response induced by damage caused by factors such as disease to living tissues resulting in an overall increase in body temperature. Localized region of higher heat production attributed to inflammation or reduced heat production due to reduced blood flow can be detected by IRT (Eddy et al., 2001). IRT has been used in several animals to determine inflammation related to changes in skin-surface temperature and to provide critical assessment of surface temperature of the target tissues (Purohit, 2006; Maldague et al., 2001).

Amezcua et al. (2014)used IRT to study sows to detect lameness and environmental condition on leg temperature values. 297 sows from commercial and research farms were evaluated visually and categorized as normal, slightly lame and obviously lame. The sows were assessed using IRT. Sows used for the study were washed and cleaned to improved accuracy of the temperature readings. Images were captured at an angle of 0^oC and a distance of 0.5 to 0.8m. Mean temperature of both hind legs were computed and analyzed. Significant variations were observed in the mean IRT temperature of the sows that were scanned. In the affected regions, differences in mean temperature were observed in the affected legs. Also some patterns were detected by IRT having significant mean temperature difference in the affected legs. The authors observed farm-to-farm differences in affected legs. This could be attributed to feeding as temperature readings were taken in commercial farms soon after feeding.

In sows, low to moderate levels lameness is difficult to detect. IRT was used to study sows to detect lameness and environmental condition on IRT leg temperature values (Amezcua, et al., 2014). 297 sows from commercial and research farms were evaluated visually and categorized as normal, slightly lame and obviously lame. The sows were assessed using IRT. Sows used for the study were washed and cleaned to improve accuracy of the temperature readings. Images were captured at an angle of 0^oC and a distance of 0.5 to 0.8m. Mean temperature of both hind legs were computed and analyzed. Significant variations were observed in the mean IRT temperature of the sows that were scanned. In the affected regions, differences in mean temperature were observed in the affected legs. Also some patterns were detected by IRT having significant mean temperature difference in the affected legs. The authors observed farm-to-farm differences in affected legs. This could be attributed to feeding as temperature readings were taken in commercial farms soon after feeding and behavioural activities of sows (Amezcua, et al., 2014).

Diseases associated with inflammation have profound effect on milk production. Mastitis, a critical disease of the udder, is associated with moderate to severe inflammation and has greater implication on milk quality and quantity and productive life of the dairy animal. Accurate and early detection of the disease is essential for appropriate treatment to be applied. There are several traditional diagnostic test for detection of mastitis including somatic cell count (SCC), culture test, California Mastitis Test (CMT) and biomarkers are subjective, invasive and time consuming. IRT provide an objective and accurate method to diagnose mastitis. Colak et al. (2008) detected mastitis in Holstein and Brown Swiss SCC and measured skin surface temperature of the udder using IRT to detect mastitis in dairy cattle for early diagnosis of mastitis at the early stage. In Gyr dairy cow, although the identification of variations of surface skin temperature of the udder at different locations was determined using IRT, the authors observed that IRT was ineffective to detect subclinical mastitis (Porcionato et al., 2011).

Infrared imaging technique has been exploited in early detection and identification of animals infected with bovine viral diarrhoea virus and foot and mouth disease virus. Foot and mouth diseases, a highly infectious viral disease affect animal hooves and require early identification for diagnosis to set up effective control measures. Gloster et al. (2011) studied 19 healthy cattle to determine coronary band temperature in the hoof and eye temperatures and determine how this vary overtime as indicators to predict early onset of foot and mouth disease. To determine possible relationship between eye and body temperature of individual animal, rectal temperature were recorded simultaneously with IRT measurements. IRT readings were taken at an operating distance of 1 – 2m and emissivity value of 0.95. Hoof temperatures of cattle were affected by ambient temperature while it has no influence on eye temperature. The authors on this basis concluded that IRT temperature of the eye is a useful indicator to predict core body temperature to detect the onset of fever in animals. Similar study was conducted by Rainwater-Lovett et al. (2009) to measure hoof temperatures of cows infected with foot and mouth disease virus before and after the onset of clinical signs. In different animal models (healthy, infected and vaccinated cattle) maximum hoof temperatures were measured throughout the duration of the infection. Threshold value was established at 34.4^{o}C to identify infected animals. The authors concluded that IRT can be used to diagnose foot and mouth disease before the appearance of symptoms.

In poultry, bumblefoot is a chronic inflammatory condition related to wet litter, wet perches and diet. Bumblefoot can result in poor growth due to lameness (Hester, 1994). Wilcox et al. (2009) studied bumblefoot in broilers by observing thermal patterns of the foot. 150 birds were studied and the temperatures of the plantar surface for each bird were recorded. Each thermogram was classified into suspect, positive or negative bumblefoot categories based on the thermal patterns on the image. The feet were assessed visually for clinical signs of bumblefoot after fourteen days of the initial imaging. Hens with no visible lesions were selected and randomly assigned into the three groups – healthy, infected and vaccinated. The thermal image category and the visual score for bumblefoot shows high correlation of 83% at fourteen days. The mean temperature difference recorded for infected hens were significantly higher than the control birds throughout the infection period. The authors observed that hens visually inspected for bumblefoot were incorrectly classified as negative. Thus, this finding suggests that visual inspection is not effective for detection of bumblefoot. However, with IRT, bumblefoot at the early stages to provide useful means to detect the disease and improve animal welfare.

Bovine viral diarrhoea disease has global impact on animal health and is difficult treatment options. However, early detection of the condition has been shown to be beneficial to enhance overall animal health. In the study Schaefer (2004) studied the potential of IRT for early detection and prediction of bovine viral diarrhoea viral (BVDV) infection using infrared thermography in cattle in controlled condition. Two groups of weaned (control and infected) calves selected used for the study. All calves were cleaned of dirt and debris beforemeasurements were taken to improve accuracy of the IRT temperature reading collected on daily basis. The calves in infected groups had higher clinical value. Temperature variation of <1^{o}C of orbital area showed possible comparative significant result similar anatomical area in uninfected group. Based on this fact, the authors suggested that there is possibility for detection of early and subclinical conditions in severe disease state which indicate the possibility for use of IRT as non-invasive tool for early BVDV detection.

3.3 REPRODUCTION

Accurate management of reproduction requires precise detection of estrus (heat) and correct timing of artificial insemination. The major factor responsible for influencing low fertility and reproduction failure is the failure to detect estrus which leads to considerable economic loss. Often, significant amount of estrus are undetected in the herd. Artificial insemination helps to achieve higher conception rate in the herd but requires accurate estrus detection. Therefore, efficient and profitable reproductive performance requires regular examination and timely breeding through artificial insemination. Traditionally, estrus detection is by visual observation which is time-consuming, laborious and challenging. Technologies including IRT can assist farmers in estrus detection.

Simõeset al. (2014) measured vulva skin temperature and gluteal skin temperature in pigs during pro-estrus and estrus using IRT to establish possible relationship between ovulation and vulvar temperature. During pro-estrus, the vulva skin temperature did not vary significantly. Highest values for the temperature difference between the vulva skin and gluteal skin temperatures was observed at 24 h and 48 h before onset of estrus while lowest values were recorded at 12 h to 6 h hours after estrus. The difference in vulva skin and gluteal skin temperature canbe a potential predictive measure of ovulation in pigs. To detect estrus and predict time of ovulation in dairy cows using temperature distribution data of vulva and muzzle, Talukder et al (2014) studied twenty dairy cattle which were artificially synchronized to come on heat. The IRT-based method predicted ovulation within 48 hours before the onset of actual ovulation in 73% of the study animals with a sensitivity of 86%. This confirms surface temperature has the potential to predict the onset of ovulation.

In a recent study by Barros de Freitas et al. (2018), surface body temperature of ewes during estrus cycle was determined by application of IRT in sheep reproduction. The authors demonstrated the potential of IRT to detect variation in surface temperature during different phases of estrus cycle in ewes. In another recent study by Vicentini et al. (2020), IRT was used to monitor surface temperature of heifers and could serve as a useful tool to monitor heifers during reproductive cycle. IRT and behavioural parameters were evaluated as possible indicators of estrus in cows (Perez Marquez et al., 2019) artificially synchronized to estrus. Behavioural activities were measured using visual camera and the thermal radiation of various body regions were represented by thermograms. Observable differences were detected between cows in estrus and pregnant cows based on thermal and behavioral patterns, thus demonstrated the viability of temperature fluctuations of various anatomical regions as well as behavioural characteristic to detect estrus in multiparous cows. Sykes et al. (2014) measured vulva skin temperature of crossbred gilts using IRT to differentiate oestrus from diestrus phase Temperature variation was observed between the vulva surface and the body with progressive increase during the estrus cycle and subsequently decline towards the ovulation period (Sykes et al., 2012).

Radigonda et al. (2017) evaluatedrate of pregnancy and ovarian activity with respect tovulva skin temperature variations measured by IRT and also determined the suitability of IRT as a tool in animal breeding. Animals were evaluated by reproductive ultrasound and corresponding thermograms were generated. Differences were observed in the mean vulva skin temperature between animals with ovarian follicles compared to those without ovarian activity, while pregnant and non-pregnant animals had similar vulva skin temperature. These results suggest that IRT could be used as a diagnostic tool to detect ovarian activity (Radigonda et al., 2017).

Spermatozoa morphology is important to itsability to fertilize the ovum to initiate embryogenesis (Saacke, 2008). Thermoregulation of blood flow around the scrotum may be influenced by changes in environmental temperature with direct impact on the quality of the semen produced. High temperature have been shown to lead to a reduction in the semen quality(Wildeus and Entwistle, 1983; Barth and Bowman, 1994) with significant influence on economic returns of livestock produced especially in sub-tropical and tropical regions (Lunstra and Coulter, 1997;

Ahmed et al., 2015). IRT has been shown to be an effective tool to monitor scrotal surface temperature. Brito et al. (2004) and Ramires Neto et al. (2011) determined the impact of ambient temperature on scrotal surface temperature. Although Kastelic et al., (1996) showed that time of day had no significant impact on scrotal surface temperature in bulls, the authors recommended that measurement of scrotal surface temperature be done prior to feeding and at least one hour after getting up to avoid false readings. In addition, the scrotal surface should be free of debris and dry to prevent artificial cooling; and the thermal camera should be placed behind the bull at a distance of approximately 1m to optimal readings (Kastelic et al., 2017).

3.4 HEAT STRESS AND MANAGEMENT

Animals experience stress from several sources including feed, infections, and ambient environment throughout production cycle. Increase in environmental temperature causes heat stress in animals due to their inability to sufficiently lose heat to maintain thermal balance with adverse impact on animal production and costs. It is undeniable that livestock are constantly exposed to stress, evident on its impact on immune function, loss of appetite, reduced feed intake, reproductive inefficiency, decreased performance and increased susceptibility to infection Occurrence of heat stress is predominant in the sub-Saharan and tropical regions. The adaptability and tolerance to heat are determined by measurement of physiological parameters (Costa et al., 2015). Animals experiencehigh body temperature which may be attributed to several factors including injury, illness, toxin, heat stress and diseases. Body temperature in animals is commonly measured by rectal temperature. This method is laborious, time consuming, invasive and requires physical contact.

IRT has the potential to measure temperature and behavioural data in animals under heat stress or infections across the entire body without physical contact. The quality of data obtained from IRT is dependent on several factors including environment, animal location, frequency of measurements, and variation in animal-to-animal activation threshold for fever or heat stress. IRT has been utilized as a tool in pigs, cattle, sheep and poultry to evaluate nutrient metabolism, detection of disease conditions, reproductive parameters, health, inflammation and stress (McManus et al., 2016). The authors concluded that the tool is highly beneficial in production environment and it provides essential information to detect thermal variation in animals. However, a caveat is that it might be limited in its capability to detect the cause associated with increase in thermal status of animals (McManus et al., 2016).

Each anatomical region has varied temperature. Generally, broilers experience tremendous stress during handling and this can be observed by temperature changes in the eye. Edgar et al. (2013) that skin surface temperature respond to routine management and have potential use in poultry to evaluate stress-induced hyperthermia. Higher temperatures in head, body, neck and wings were recorded for birds in high and moderate stocked house compared to low house density with negative impact on poultry performance and welfare (Abudabos et al., 2013). Moreover, skin surface temperature in broilers provided information on their thermal state which may assist diagnosis of stress conditions, while persistent exposure to high ambient temperature significantly decreased performance (Giloh et al., 2012).

IRT has been employed in dairy and beef cattle to determine heat stress (Salles et al., 2016; Unruh et al., 2017). The use of IRT is an objective tool that can be utilized to identify heat-stressed feedlot calves but not those that might possibly experience heat stress in early morning (Unruh et al., 2017). Rocha et al. (2019) studied the best anatomical sites for IRT readings in pigs. The study animals were subjected to stresscondition during handlingand transportation with the temperature readings recorded from different parts including rump, behind the ears, orbital region, and neck.Pigs response to handling resulted in increased body surface temperature with the orbital region and behind the ears identified as the best anatomical sites for IRT readings (Rocha et al. 2019).

The rate of heat exchange in poultry between the bird and the surrounding environment is regulated by their feather which acts as thermal protection. IRT is a potential tool for objective and quantitative assessment of the conditions of laying-hen feathers and also quantify surface temperature profiles of laying hens (Zhao et al., 2013). McCoard et al. (2014) in their study applied IRT to measure heat loss from newborn lambs. The thermal camera captures continuous thermal images of newborn lambs at various instances. They concluded that IRT is a sensitive method to measure heat loss from newborn lambs (McCoard et al., 2014).

The capacity of newly born lambs to regulate their body temperature when subjected to cold challenge at 1 h and 4 h after birth was investigated (Labeur et al., 2017). Lambs born to ewes shorn late in their pregnancy were compared to the control lambs born to ewes not shorn. Thermal images were taken every 10 mins during the cold challenge. Analysis of the data showed that the lambs born to shorn ewes were able to maintain their body temperature compared to the control lambs. The authors were unable to determine whether increase surface temperature contributes to heat loss or acts as a means by which the lambs were able to maintain internal body temperature when exposed to cold temperature.

It is therefore, a fact that IRT has diverse application in livestock production and has the potential as non-invasive and non-contact tool to measure body temperature for assessment of health status and enhanceoverall livestock productivity.

4.0 MACHINE LEARNING ALGORITHM

The increasing use of technology in livestock production has led to exponential growth in the volume of data generated. This may be attributed to increased knowledge of how data-driven technologies might be used to support decision making and enhance productivity. Examining big dataset to generate knowledge can be achieved using machine learning. Machine learning (ML), a field of artificial intelligence, has been used to solve problems that human solve intuitively. It is based on a set of algorithms and techniques that automatically identify patterns within data and build predictive models from the data.

ML algorithms sift through high volumes of big data to identify patterns to support decision making. This process of learning patterns from input data is known as training. During model training, the learning algorithm maps input variable (features) to output labels. The model is then tested on another subset of the input data to validate its performance. The input data to a ML model consist of several features and labels. Features represent a certain value for all data points in a dataset. Features, which could be raw data or data that has been transformed mathematically, can be continuous, categorical or binary. Labels, the values the ML model aim to predict, can be binary or categorical.

ML algorithms are trained in one of two ways including supervised and unsupervised learning. Supervised learning involves the use of known training labels as a guide to train the model. Since the target output is known, the learning model easily define discriminating features that can map input to the correct target class. Supervised learning can either be classification or regression. Classification is used to predict discrete values of target classes while regression is used to predict continuous values of target classes. Algorithms commonly used for supervised training include support vector machine, k-nearest neighbour and artificial neural network.

Support Vector Machine, SVM finds the best decision boundary (hyperplane) that divides data set into two regions or groups. SVM identifies all data points closest to the separating hyperplane, called support vectors which are used for predictive purposes. SVM is best suited for predicting two target output classes such as diseased or non-diseased; hot or cold.

The k-nearest neighbour (kNN) algorithm is a non-parametric classification method that classifies a data point into a category based on the category of k-number of nearest neighbour data points. The algorithm assumes that similar data points are in close proximity to each other. The similarity is computed based on mathematical distance including euclidean, chebychev and hamming distances. The kNN algorithm is a simple but powerful learning algorithm that can learn to classify multiple target output classes. The performance of the algorithm diminishes with increased volume of data.

Another commonly used learning model is the artificial neural network. The artificial neural network simulates the process of operation of a neuron found in biological brain. The artificial neural network consists of three layers – the first or input layer, middle or hidden layer and the last or output layer. Each layer consists of weighted, interconnected units of computation or neurons. Within the network, signals are sent from the input nodes to hidden nodes through weighted connections, and on to output nodes through the more weighted connections. This process is known as forward propagation. The predicted value at the output node is compared with the target output using a loss function to determine error rate. During training, the error rate is sent back through the network to adjust the weighted connections in order to reduce the error rate. This process is known as back propagation. The process of back propagation is repeated until the error rate is sufficiently low at which training is stopped and the final value is output as the predicted value.

During unsupervised learning, ML algorithms automatically determine discriminating features that can be used to classify or categorize the input data into target classes. This is done without any hints from the input data. An example of such task is data segmentation where the learning model attempts to group the input data into segments or clusters. When applied to image data, the image is demarcated based on the properties of objects within the image. Segmentation is a useful tool to identify objects within an image and has been widely used in tracking animals, animal identification and counting animal population (Purhamet al., 2018; Chabot et al., 2018; Choudhury et al., 2020; Kim and Hidaki, 2021). Segmentation can be achieved using three techniques including thresholding, edge-based and region-based segmentation techniques.

Thresholding segmentation technique segments objects in the image based on pixel intensity. A pixel is a point in an image and assigned a value based on the colour of that point in the image.

Thresholding sets the value of a pixel to either white or black (1 or 0). This results in a black and white image. Thresholding separates the background of an image from its foreground providing contrast between the background image and the object within the image thus segmenting the objects in the image. Edge-based segmentation is another segmentation technique, which utilizes borders or edges present in an image as a basis for segmentation. An edge is a pixel with sharp changes in brightness or intensity. Typically, the edges in an image are often in the form of curved line segments. Edge-based techniques detect and connect edges to form contours which highlight the boundaries of objects within the images. Region-based segmentation technique separates similar pixels in an image into regions. This method of segmentation separates an input data based on value similarity and spatial proximity of the pixels in the image. Pixels with similar values and in close proximity are grouped into regions. These regions form segments within the image.

ML algorithms have limited capacity to process natural data in raw form. Typically, the data is often transformed in some way to enable the ML model to extract features that can be used for predictive purposes. A robust ML algorithm is able to make accurate predictions for previously unseen data, a process known as generalization. This involves using the knowledge learnt from the training data to make predictions on other datasets which possess similar characteristics. Deep learning algorithms utilize a form of learning called representation learning. This ensure that the algorithm automatically detect representation of the data that can be used to make predictions. Deep learning algorithms utilize deep architectures of interconnected neural networks. In a deep learning network, there are two or more layers between the input and output layers. Each successive layer in a deep network learns a more refined representation of the data than prior layers leading to a hierarchical method of extracting predictive patterns from the data. Artificial neural networks with more hidden layers can solve more complex tasks to produce more accurate results.

Convolutional neural network, CNN, is a form of deep learning algorithm which has extensive application in image processing (Hershey et al., 2017; He et al., 2017). CNN use convolution, a special type of mathematical operation, instead of general matrix operation in at least one layer of its network. The convolutional neural network has been widely applied to image classification (Hershey et al., 2017) and segmentation tasks (He et al., 2017), which makes it suitable for use in agricultural tasks.

5.0 INTEGRATION OF MACHINE LEARNING WITH INFRARED THERMOGRAPHY

Farm animals are constantly monitored for ill health, stress and performance. ML has been used to analyze IRT data to promote animal welfare, animal tracking and monitoring, identifying stress, pain and inflammation in animals.

Breathing patterns is a method commonly used to determine the health status of animal. It helps to determine if the animal is suffering pain, stress, or disease. A common way of determining breathing patterns is through the use of stethoscope which may require handling and restraining the animal which could excite the animal and affect its breathing pattern. To overcome these limitations, Kim and Hidaka (2021) proposed the use of IRT and a form of deep learning algorithm, Mask R-CNN, for nose detection to determine breathing rates and breathing patterns in cattle. The thermal images were segmented using Mask R-CNN,to identify cattle nose.

Thermal fluctuations around the nose during inhalation and exhalation were monitored to determine the respiration rate per minute for each animal. The authors suggested that infrared and deep learning algorithm can be adopted to determine varied breathing patterns in cattle that could be used to detect stress and pain in animals.

Jaddoa et al. (2020) developed a method to automatically detect faces of cattle in thermograms. Thermograms in grey format were obtained for each animal. The image was enhanced for brightness and intensity. The face of each animal was isolated using windows of different sizes and scale. The Histogram of Oriented Gradient (HOG) was computed to extract features that distinguish each face from the background in each image. The HOG values were input to SVM to learn to detect faces in the thermograms. The authors concluded that the proposed method performed better than existing methods which proved cattle faces can be automatically detected from thermograms using ML.

Thermoregulatory responses of dairy buffaloes before and after milking were investigated (Sevegnani et al., 2016). Skin surface temperatures were taken by infrared thermometers and thermal camera, as well as each respiratory rate. Other data collected include black globe temperatures, radiating thermal load values to determine the thermal conditions of milking room. These data was input into ANN to determine the best feature to that can predict thermal comfort. The authors concluded that thermal comfort in dairy buffaloes can be predicted using skin surface.

Thermal images of dairy cow were processed using ML as non-invasive approach to identify cattle (Bhole et al., 2019). The authors developed a processing pipeline comprised of image processing, computer vision, and ML techniques to learn distinctive coat patterns to identify individual animals. They suggested that this method could be adopted to distinguish coat pattern of farm animals to identify individual animals uniquely. (Bhole et al., 2019).

6.0 CONCLUSION

Livestock animals are faced with enormous challenges affecting their health, productivity and overall economic returns. IRT provides a quick non-invasive non-contact method to remotely measure body surface temperature of animals to determine their state of health and general welfare. Thermograms generated in real time create large volumes of data and when analyzed can provide farmers with insight to make informed decisions and improve management decisions. Much information has been published on the benefits of IRT to improve animal productivity. However, productivity can be greatly improved with end-to-end system that can process vast amount of thermal data and provide accurate information to assist in decision making. ML algorithms provide a means to quickly and accurately process data to create models that learn to identify patterns in data which can be used for future predictions.The use of ML algorithms with IRT had been applied in animal identification, animal face detection, prediction of pain from breathing patterns and onset of stress in animals. Therefore, the integration of IRT and ML algorithms provide a powerful tool to enhance early diagnosis of disease and non-diseased conditions in livestock production to support decision making.

REFERENCES

Abdelhamid N . and Sougrati B ., 2021.Modeling of the horizontal and vertical anomalies in a Reinforced concrete slab and its detection by using infrared thermography method .Journal of Engg.Research. 9(1): 86-104` https://doi.org/10.36909/jer.v9i1.8312

Abudabos, A.M., Samara, E.M., Hussein, E.O.S. etalet al., 2013. Impacts of stocking density on the performance and welfare of broiler chickens. Ital. J. Anim. Sci. 12 (11), 66–71. http://dx.doi.org/10.4081/ijas.2013.e11.

Abuelo, A., Gandy, J.C., Neuder, L., et al., 2016. Short communication: Markers of oxidant status and inflammation relative to the development of claw lesions associated with lameness in early lactation cows. Journal of Dairy Science. 99:5640–5648.

Ahmed, A., Tiwari, R.P., Mishra, G.K., et al., 2015.Effect of Environmental heat stress on reproduction performance of dairy cows - A review.International Journal of Livestock Research. 5(4):10-18.

Alsaaod, M. and Büscher, W., 2011.Detection of hoof lesions using Digital Infrared Thermography in dairy cows. Journal of Dairy Science, 95:735-742

Alsaaod, M., Schaeffer, A. L., Büscher, W. and Steiner, A., 2015.The role of infrared thermography as a non-invasive tool for the detection of lameness in cattle. Sensors, 15:14513–14525.

Amezcua, R., Walsh, S., Luimes, P. H. and Friendship, R. M., 2014. Infrared thermography to evaluate lameness in pregnant sows. Canadian Veterinary Journal La Revue VétérinaireCanadienne 55(3):268–272

Barros de Freitas, A. C., Ortiz Vega, W. H., Quirino, C.R. et al., 2018. Surface temperature of ewes during estrous cycle measured by infrared thermography.Theriogenology.Oct 1; 119:245-251. doi:10.1016/j.theriogenology.2018.07.015

Barth, A. D. and Bowman, P. A., 1994.The sequential appearance of sperm abnormalities after scrotal insulation or dexamethasone treatment in bulls.Canadian Veterinary Journal. 35(2):93-102.

Bhole A., Falzon O., Biehl M. and Azzopardi G., 2019. A Computer Vision Pipeline that Uses Thermal and RGB Images for the Recognition of Holstein Cattle. In: Vento M., Percannella G. (eds) Computer Analysis of Images and Patterns. CAIP 2019. Lecture Notes in Computer Science, vol 11679. Springer, Cham. https://doi.org/10.1007/978-3-030-29891-3_10.

Bobić T., Mijić, P., Gregić, M., et al., 2017. Early detection of the hoof diseases in Holstein cows using thermovision camera. Agriculturae Conspectus Scientificus, 82 (No.2):197–200.

Brito, L. F. C., Silva, A. E. D. F., Barbosa, R. T., Kastelic, J. P., 2004. Testicular thermoregulation in Bosindicus, crossbred and Bostaurus bulls: relationship with scrotal, testicular vascular cone and testicular morphology, and effects on semen quality and sperm production. Theriogenology 61(2–3):511–528.

Byrne, D. T., Berry, D. P., Esmonde, H., McGovern, F., Creighton, P. and McHugh, N., 2019.Infrared thermography as a tool to detect hoof lesions in sheep.Translational Animal Science. 3:577–588. doi:10.1093/tas/txy132

Chabot, D., Dillon, C. , and Francis, C. M., 2018. An approach for using off-the-shelf object-based image analysis software to detect and count birds in large volumes of aerial imagery. Avian Conservation and Ecology 13(1):15. doi:10.5751/ACE-01205-130115.

Choudhury M., Saikia T., Banik S., Patil, G., S. R., Pegu,et al 2020 Infrared imaging a new non-invasive machine learning technology for animal husbandry. The Imaging Science Journal, 68(4):240-249, doi:10.1080/13682199.2020.1848084

Colak, A., Polat, B., Okumus, Z., et al., 2008. Short communication: early detection of mastitis using infrared thermography in dairy cows. Journal of dairy science, 91(11), 4244–4248. https://doi.org/10.3168/jds.2008-1258
Cook, N.B., Rieman, J., Gomez, A. and Burgi, K., 2012. Observation on the design and use of footbaths for the control of infectious hoof disease in dairy cattle. The Veterinary Journal, 193:669–673.
Costa, A. N. L., Feitosa, J. V., Montezuma Jr, P. A., Souza, P. T. and Araújo, A. A., 2015. Rectal temperatures, respiratory rates, production, and reproduction performances of crossbred Girolando cows under heat estresse in northeastern Brazil. Int. J. Biometeorol. 59 (11):1647–1653. doi:10.1007/s00484-015-0971-4.
de Lima, V., Piles, M., Rafel, O., et al., 2013. Use of infrared thermography to assess the influence of high environmental temperature on rabbits. Research in veterinary science, 95(2):802–810. doi:10.1016/j.rvsc.2013.04.012
Eddy, A. L., Van Hoogmoed, L. M. and Snyder, J. R., 2001.The role of thermography in the management of equine lameness.Veterinary Journal. 162 (3):172–181. doi:10.1053/tvjl.2001.0618
Edgar, J.L., Nicol, C.J., Pugh, C.A., and Paul, E.S., 2013. Surface temperature changes in response to handling in domestic chickens. Physiol. Behav. 119:195–200.
Ferreira, M.S., Goes, R.H.T.B., Martinez, A.C. et al., 2020. Infrared thermography and feeding behavior of lambs fed increasing levels of safflower grains. Rev. bras. saúde prod. anim., RevistaBrasileira de Saúde e Produção Animal, 21, e2121232020.Epub October 30, 2020.https://doi.org/10.1590/s1519-99402121232020
Ferreira, V.M.O.S., Francisco, N.S., Belloni, M.et al., 2011. Infrared thermography applied to the evaluation of metabolic heat loss of chicks fed with different energy densities. Brazilian Journal of Poultry Science, 13(2), 113-118. https://doi.org/10.1590/S1516-635X2011000200005
Franchi, G.A., Jensen, M.B., Herskin, M.S. et al., 2021. Assessing response to dry-off in dairy cows kept outdoors using spontaneous behaviours and infrared thermography—a pilot study. Trop Anim Health Prod 53, 46 https://doi.org/10.1007/s11250-020-02487-0 .
García – Munoz, A., Singh, N., Leonardi, C. and Silva-Del-Rio, N., 2017.Effect of hoof trimmer intervention in moderately lame cows on lameness progression and milk yield. J. of Dairy Science 100:9205–9214. doi:10.3168/jds.2016-12449.
Gianesella, M., Arfuso, F., Fiore, E., Giambelluca, S., Giudice, E., Armato, L., and Piccione, G., 2018.Infrared thermography as a rapid and non-invasive diagnostic tool to detect inflammatory foot diseases in dairy cows.Polish Journal of Veterinary Sciences. 21(2):299–305. doi:10.24425/122597
Giloh, M., Shinder, D., and Yahav, S., 2012. Skin surface temperature of broiler chickens is correlated to body core temperature and is indicative of their thermoregulatory status. Poultry Science, 91(1), 175–188. doi:10.3382/ps.2011-01497
Gloster, J., Ebert, K., Gubbins, S., et al., 2011. Normal variation in thermal radiated temperature in cattle: implications for foot-and-mouth disease detection. BMC Veterinary Research 7:73. doi:10.1186/1746-6148-7-73
Gonçalves, C.B., Leles, A.C.Q., Oliveira, L.E., Guimaraes, G., Cunha, J.R. and Fernandes, H., 2019. Machine Learning and Infrared Thermography for Breast Cancer Detection. Proceedings 27:45. https://doi.org/10.3390/proceedings2019027045

He, K., Gkioxari, G., Dollar P., and Girshick, R., 2017. Mask R-CNN. In: 2017 IEEE International Conference on Computer Vision (ICCV) Oct 2017, Venice pp: 2980-2988. doi:10.1109/ICCV.2017.322.
Hershey S., Chaudhuri S., Ellis D.P.W., Gemmeke, J.F. et al., 2017. CNN architectures for large-scale audio classification. In: 2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), New Orleans, LA, 2017, pp. 131-135, doi:10.1109/ICASSP.2017.7952132.
Hester, P. Y., 1994. The role of environment and management on leg abnormalities in meat-type fowl.Poultry Science. 73:904–915.
Jaddoa, M., Gonzalez, L., Cuthbertson, H. and Al-Jumaily, A., 2020 Multi View Face Detection in Cattle Using Infrared Thermography. In: Khalaf M., Al-Jumeily D., Lisitsa A. (eds) Applied Computing to Support Industry: Innovation and Technology. ACRIT 2019.Communications in Computer and Information Science, vol 1174.Springer, Cham. https://doi.org/10.1007/978-3-030-38752-5_18
Jansson, A., Lindgren, G., Velie, B.D., and Solé, M., 2021. An investigation into factors influencing basal eye temperature in the domestic horse (Equuscaballus) when measured using infrared thermography in field conditions. Physiology and Behavior, 228, 113218. https://doi.org/10.1016/j.physbeh.2020.113218
Kammersgaard, T. S., Malmkvist, J., and Pedersen, L. J., 2013. Infrared thermography--a non-invasive tool to evaluate thermal status of neonatal pigs based on surface temperature. Animal. 2013 Dec;7(12):2026-34. doi: 10.1017/S1751731113001778. PMID: 24237678.
Karp, D., 2020. Detecting small and cryptic animals by combining thermography and a wildlife detection dog.Sci Rep 10, 5220. https://doi.org/10.1038/s41598-020-61594-y
Kastelic, J. P., Cook, R. B., Coulter, G. H., Wallins, G. L. and Entz T., 1996. Environmental factors affecting measurement of bovine scrotal surface temperature with infrared thermography. Animal Reproduction Science 41:153–159.
Kastelic, J. P., Wilde, R. E., Rizzoto, G. and Thundathil, J.C., 2017. Hyperthermia and not hypoxia may reduce sperm motility and morphology following testicular hyperthermia. VeterinarniMedicina 62:437–442
Keyserlingk, M.A., Rushen, J., Passillé, A.M. and Weary, D.M., 2009.Invited review: The welfare of dairy cattle – Key concepts and the role of science.Journal of Dairy Science. 92:4101–4111.
Kim, S. and Hidaki, Y., 2021.Breathing Pattern Analysis in Cattle Using Infrared Thermography and Computer Vision.Animals 11, 207.doi:10.3390/ani11010207
Koltes, J. E., Koltes, D. A., Mote, B. E., et al., 2018. Automated collection of heat stress data in livestock: New technologies and opportunities. Translational Animal Science. 2018.2:319–323. doi:10.1093/tas/txy061
Kunc, P., Kníz˘ková, I., Pr˘ikryl, M., Maloun, J., 2007. Infrared thermography as a tool to study the milking process: a review. AgriculturaTropicaetSubtropica 40 (1):29–32
Labeur, L., Villiers, G., Small, A. H., et al., 2017.Infrared thermal imaging as a method to evaluate heat loss in newborn lambs.Research in veterinary science, 115, 517–522. https://doi.org/10.1016/j.rvsc.2017.09.023
LokeshBabu, D. S., Jeyakumar, S., Vasant, P. J., Sathiyabarathi, M., Manimaran, A., Kumaresan, A., Pushpadass, H. A., Sivaram, M., Ramesha, K. P., Kataktalware, M. A., and Siddaramanna 2018. Monitoring foot surface temperature using infrared thermal imaging for assessment of

hoof health status in cattle: A review. Journal of Thermal Biology, 78:10–21. doi:10.1016/j.jtherbio.2018.08.021

Lowe, G. L., Sutherland, M. A., Waas, J. R., et al., 2019.Physiological and behavioral responses as indicators for early disease detection in dairy calves. Journal of dairy science, 102(6), 5389–5402

Lunstra, D.D. and Coulter, G.H., 1997. Relationship between scrotal infrared temperature patterns and natural-mating fertility in beef bulls.Journal of Animal Science. 75(3):767-774.

Magnani, D., Gatto, M., Cafazzo, S., et al., 2011.Difference of surface body temperature in piglets due to the backtest and environmental condition. In: Conference Proceedings of International Society for Animal Hygiene: July 6, 2011, Vienna. p. 1029–32.

Maldague, X. P. V., Jones, T. S., Kaplan, H., Marinetti, S., and Prystay, M., 2001. Fundamentals of Infrared and Thermal Testing. Nondestructive Handbook: Infrared and Thermal Testing. 3rd Ed. ASNT Press, Columbus, OH, pages 15–34.

Martins, R. F. S., Paim, T. P., Cardoso, C. A., Dallago, B. S. L., Melo, C. B., Louvandini, H., and Mcmanus, C., 2013. Mastitis detection in sheep by infrared thermograpy. Research in Veterinary Science 94 (3), 722–724. 2013. http://dx.doi.org/10.1016/j.rvsc.2012.10.021.

Martins, R.F.S., Paim, T.P., Cardoso, et al., 2013.Mastitis detection in sheep by infrared thermograpy. Research in Veterinary Science 94 (3):722–724. doi:10.1016/j.rvsc.2012.10.021

McCoard, S.A., Henderson, H.V., Knol, F.W., et al., 2014 Infrared thermal imaging as a method to study thermogenesis in the neonatal lamb. Animal Production Science 54, 1497-1501.

McManus, C., Tanure, C.B., Peripolli, V., Seixas, L., Fischer, V., Gabbi, A.M., Menegassi, S.R.O., Stumpf, M.T., Kolling, G.J., Dias, E. and Costa, J.B.G., 2016. Infrared thermography in animal production: An Overview. Computers and Electronics in Agriculture, 123:10-16

McNamee, P. T. and J. A. Smyth., 2000. Bacterial chondronecrosis with osteomyelitis (‘femoral head necrosis’) of broiler chickens: A review. Avian Pathology. 29:253–270.

Montanholi, Y.R., Nicholas, E.O., Kendall, C.S., et al., 2008. Application of infrared thermography as an indicator of heat and methane production and its use in the study of skin temperature in response to physiological events in dairy cattle (Bostaurus). Journal of Thermal Biology 33 (8), 468–475. doi:10.1016/j.jtherbio.2008.09.001

Nahm F.S., 2013. Infrared thermography in pain medicine. The Korean Journal of Pain, 26(3), 219–222. https://doi.org/10.3344/kjp.2013.26.3.219

Nascimento, G.R., Nääs, I.A., Baracho, M.S., et al., 2014.Infrared thermography in the estimation of thermal comfort of broilers. Rev. Bras. Eng. Agríc.Ambient. 18 (6), 658–663. http://dx.doi.org/10.1590/S1415-43662014000600014

Parham, J., Stewart, C., Crall, J., Rubenstein, D., Holmberg, J. and Berger-Wolf, T., 2018.An Animal Detection Pipeline for Identification. In: 2018 IEEE Winter Conference on Applications of Computer Vision (WACV), Lake Tahoe, NV, pp. 1075-1083, doi:10.1109/WACV.2018.00123.

Pérez de Diego, A.C., Sánchez-Cordón, P.J., Pedrera, M. et al., 2013. The use of infrared thermography as a non-invasive method for fever detection in sheep infected with bluetongue virus. Veterinary.Journal. 198:182–186.

Perez Marquez, H.J., Ambrose, D.J., Schaefer, A.L., et al., 2019. Infrared thermography and behavioral biometrics associated with estrus indicators and ovulation in estrus-synchronized dairy cows housed in tiestalls. Journal of Dairy Science, 102(5), 4427–4440. https://doi.org/10.3168/jds.2018-15221

Pezeshki, A., Stordeur, P., Wallemacq, H., et al., 2011.Variation of inflammatory dynamics and mediators in primiparous cows after intramammary challenge with Escherichia coli. Veterinary Research 42:15, 1–10. doi:10.1186/1297-9716-42-15

Porcionato, M.A., Canata, T.F., and Oliveira, C.E.L. and Santos, M.V.D., 2011. Udder thermography of gyr cows for subclinical mastitis detection / termografia do úbere de vacasgir para detecção de mastitesubclínica. RevistaBrasileira de Engenharia de Biossistemas. 3. 251. 10.18011/bioeng2009v3n3p251-257.

Purohit, R. C., 2006. Use of Infrared Imaging in Veterinary Medicine.Biomedical Engineering Handbook.3rd Ed. J. D. Bronzino, ed. Taylor and Francis, London, UK.

Radigonda, V. L., Pereira, G. R., da Cruz Favaro, P., BarcaJúnior, F. A., Borges, M., Galdioli, V., and Júnior, C. K., 2017. Infrared thermography relationship between the temperature of the vulvar skin, ovarian activity, and pregnancy rates in Braford cows. Tropical Animal Health And Production, 49(8):1787–1791. doi:10.1007/s11250-017-1378-5

Rainwater-Lovett, K., Pacheco, J.M., Packer, C. and Rodriguez, L.L., 2009. Detection of foot-and-mouth disease virus infected cattle using infrared thermography. Veterinary Journal., 180:317–324.

RamiresNeto, C., Rodello, L. and Bicudo, S. D., 2011. Scrotal thermography in prepubertalovines submitted to heat stress. Veterinária e Zootecnia 18 (4):1017–1019.

Roberto, J.V.B., Souza, B.B., Delfino, L.J.B. and Marques, B.B., 2014.Thermal gradients and physiological responses of goats in the Brazilian semi-arid using thermography infrared.Journal of Animal Behaviour and Biometeorologia. 2 (1):11–19.

Rocha, Luiene and Devillers, Nicolas and Maldague, Xavier and Kabemba, Fidèle and Fleuret, Julien and Guay, Frederic and Faucitano, Luigi., 2019. Validation of Anatomical Sites for the Measurement of Infrared Body Surface Temperature Variation in Response to Handling and Transport.Animals. 9. 425. 10.3390/ani9070425.

Rodríguez, A.R., Olivares, F.J., Descouvieres, P.T., et al., 2015.Thermographic assessment of hoof temperature in dairy cows with different mobility scores. Livestock Science184:92–96.

Rogalski, A., 2012. History of infrared detectors.Opto-Electronics Review 20, 279-308

Saacke, R. G., 2008. Sperm morphology: Its relevance to compensable and uncompensable traits in semen. Theriogenology 70:473-478

Salles, M. S, da Silva, S. C., Salles, F. A., Roma, L. C. Jr, El Faro, L., Bustos Mac Lean, P. A., Lins de Oliveira, C. E. and Martello, L. S., 2016. Mapping the body surface temperature of cattle by infrared thermography. J Therm Biol. 2016 Dec;62(Pt A:63-69. doi: 10.1016/j.jtherbio.2016.10.003. Epub 2016 Oct 21. PMID: 27839551.

Schaefer, A.L., Cook, N.J., Tessaro, S.V. et al., 2004.Early detection and prediction of infection using infrared thermography. Can. J. Anim. Sci. 84, 73–80.

Schaefer, A.L., Matthews, L.R., Cook, N.J., et al., 2002.Novel noninvasive measures of animal welfare. In: Animal Welfare and Behaviour: From Science Solution, Joint NAWAC/ISAE Conference. 27–28 June 2002. Hamilton, New Zeland.

Schlageter-Tello, A., Bokkers, E.A.M., GrootKoerkamp, P.W.G., VanHertem, T., Viazzi S., Romanini, C. E. B., Halachmi, I., Bahr, C., Berckmans, S. and Lokhorst, K., 2014. Manual and automatic locomotion scoring systems in dairy cows: A review. Preventive Veterinary Medicine. 116:12–25.

Schneider, M., Ziegler, T. and Kolter, L., 2020.Thermoregulation in Malayan sun bears (Helarctosmalayanus) and its consequences for in situ conservation.Journal of Thermal Biology, 91, 102646. https://doi.org/10.1016/j.jtherbio.2020.102646

Sevegnani, K.B., Fernandes, D.P.B., and Silva, Silvia H. Modenese-Gorla da., 2016. Evaluation of thermorregulatory capacity of dairy buffaloes using infrared thermography.EngenhariaAgrícola, 36(1), 1-12. https://doi.org/10.1590/1809-4430-Eng.Agric.v36n1p1-12/2016

Siewert, C., Dänicke, S., Kersten, S., et al., 2014.Difference method for analysing infrared images in pigs with elevated body temperatures.ZeitschriftfürMedizinischePhysik. 24 (1), 6–15.

Simões, V.G., Lyazrhi, F., Picard-Hagen, N., Gayrard, V., Martineau, G.P., WaretSzkuta, A., 2014.Variations in the vulvar temperature of sows during proestrus and estrus as determined by infrared thermography and its relation to ovulation.Theriogenology 82(8):1080–1085. doi:10.1016/j.theriogenology.2014.07.017

Soerensen, D.D. and Pedersen, L.J., 2015. Infrared skin temperature measurements for monitoring health in pigs: a review. ActaVeterinariaScandinavica. 57(1): 1–11. doi:10.1186/s13028-015-0094-2.

Soerensen, D.D., Clausen, S., Mercer, J.B. and Pedersen, L.J., 2014. Determining the emissivity of pig skin for accurate infrared thermography. Computers and Electronics in Agriculture 109:52–58. doi:10.1016/j.compag.2014.09.003

Soroko M., Howell K., 2018. Infrared Thermography: Current Applications in Equine Medicine. Journal of Equine Veterinary Science, 60: 90-96. doi:10.1016/j.jevs.2016.11.002.

Soroko, M. and Zaborski, D., 2020.Investigation of the effects of probiotic, Bacillus subtilis on stress reactions in laying hens using infrared thermography.PLoS ONE 15(6):e0234117. doi:10.1371/journal. pone.0234117

Speakman, J.R. and Ward, S., 1998. Infrared thermography: principle and applications. Zoology. 101:224–232.

Stewart, M., Webster, J.R., Stafford, K.J., et al., 2010. Technical note: effects of an epinephrine infusion on eye temperature and heart rate variability in bull calves. Journal of Dairy Science 93:5252–7

Sykes, D.J., Couvillion, J.S., Cromiak, A. et al 2012. The use of digital infrared thermal imaging to detect estrus in gilts.Theriogenology 78:147-152.

Sykes, D.J., Couvillion, J.S., Cromiak, A., et al., 2012.The use of digital infrared thermal imaging to detect estrus in gilts.Theriogenology. 78. 147-52. 10.1016/j.theriogenology.2012.01.030.

Talukder, S., Kerrisk, K. L., Ingenhoff, L., Thomson, P. C., Garcia, S. C. and Celi, P., 2014. Infrared technology for estrus detection and as a predictor of time of ovulation in dairy cows in a pasture-based system. Theriogenology, 81(7):925–935. doi:10.1016/j.theriogenology.2014.01.009

Unruh, E.M., Theurer, M.E., White, B.J., Larson, R.L., Drouillard, J.S. and Schrag, N., 2017.Evaluation of infrared thermography as a diagnostic tool to predict heat stress events in feedlot cattle. Am. J. Vet. Res. 78:771–777. https://doi.org/10.2460/ajvr.78.7.771

Vicentini, R.R., Montanholi, Y. R., Veroneze, R. et al., 2020. Infrared thermography reveals surface body temperature changes during proestrus and estrus reproductive phases in Gyr heifers (Bostaurusindicus), Journal of Thermal Biology, Volume 92, 102662, ISSN 0306-4565, doi:10.1016/j.jtherbio.2020.102662 .

Weimer, S. L., Wideman, R. F., Scanes, C. G., et al., 2019. The utility of infrared thermography for evaluating lameness attributable to bacterial chondronecrosis with osteomyelitis.Poultry Science. 98:1575-1588.

Weimer, S. L., Wideman, R. F., Scanes, C. G., Mauromoustakos, A., Christensen, K. D., and Vizzier-Thaxton, Y., 2020. Broiler stress responses to light intensity, flooring type, and leg weakness as assessed by heterophil-to-lymphocyte ratios, serum corticosterone, infrared thermography, and latency to lie.Poultry Science, 99(7), 3301–3311. doi:10.1016/j.psj.2020.03.028
Weschenfelder, A.V., Maldague, X., Rocha, L.M., et al., 2014. The use of infrared thermography for pork quality prediction.Meat Science. 96 (1):120–125. doi:10.1016/j.meatsci.2013.05.047
Wilcox, C., Patterson, J., and Cheng, H. W., 2009.Use of thermography to screen for subclinical bumblefoot in poultry. Poultry Science, 88(6):1176-80 .
Wildeus, S. and Entwistle, K. W., 1983. Spermiogram and sperm reserves in hybrid Bosindicus x Bostaurus bulls after scrotal insulation. Journal of Reproduction and Fertility. 69:711-716
Zhao, Y., Xin, H. and Dong, B., 2013. Use of infrared thermography to assess laying-hen feather coverage.Poultry science, 92(2), 295–302. https://doi.org/10.3382/ps.2012-02629