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Cattle Disease Detecting IoT Thermographic System

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Abstract – **The food industry is facing enormous challenges in order to ensure sufficient amounts of food for the expanding population, while meeting and fulfilling rapidly changing quality demands. With cattle being one of the essential food-supplying animal breeds, imposed are strict requirements towards their wellbeing support and monitoring. Within this work a novel developed IoT based thermographic system for cattle disease detection is presented, which allows scalability and direct farming applicability. Emphasis is additionally pointed towards methods for parasitic effects' cancellation.**

Keywords– **Artificial intelligence; cattledisease detection; cloud computing; IoT; thermography**

I. INTRODUCTION

With the advances in electronics, computing and telecommunications, people are gradually being replaced in many fields by artificial intelligence (AI). In many industries the direct involvement of people drastically reduces the effectiveness of the enterprises and the quality of the production. The introduction of AI speeds up activities and improves upon accuracy in many areas, where it would be impossible with the participation of people.

Considering recent information analysis, AI jobs postings within the United States for 2020 - the leading AI-related positions are being directed firstly towards the IT industry, and secondly towards professional, scientific, and tech services. But closely behind in third place are industrial branches which generally are not related to artificial intelligence such as: agriculture, forestry, fishing, and hunting, because of the massive workforce employed by them [1]. The trend is depicted in Fig. 1.

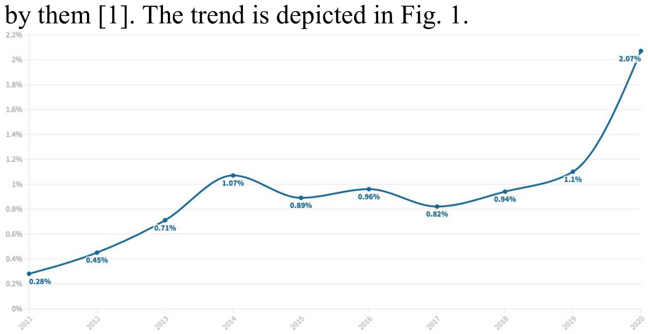

Fig. 1. The trend in AI jobs postings within the agriculture, forestry, fishing, and hunting industries [1]

This information proves the fact that the gradualadoption of new technologies is mandatory for achieving progress in all industrial fields. The food industry faces a lot of challenges and pressure aimed towards ensuring enormous amounts of products for the increasing population, with requirements for fulfilling changing quality demands.

Amongst the most commonly bred livestock are cattle, due to the large amounts of milk that they are able to give. Fig. 2 shows a statistical excerpt describing the produced quantity of milk for the largest dairy producing countries during the period 2010-2018.

Yearly milk production by country [million tons]

	2010	2011	2012	2013	2014	2015	2016	2017	2018
India	121.8	127.9	132.4	137.7	146.3	155.5	165.4	176.3	187.7
USA	87.488	89.020	91.01	91.29	93.462	94.578	96.367	97.762	98.688
China	30.5	31.2	32.35	34.5	36.7	37.5	38.0	38.1	39.6

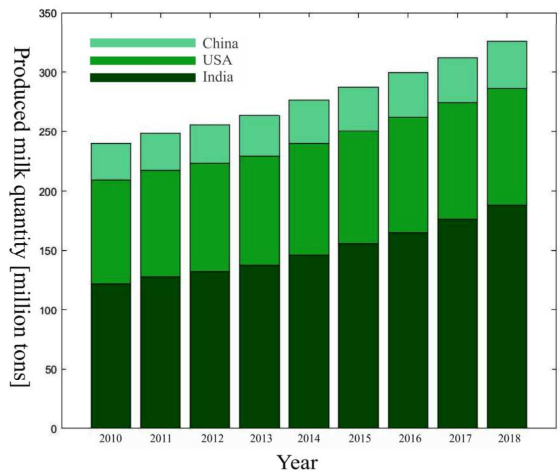

Fig. 2. Dairy production during the period 2010-2018 of India, USA and China

Average yearly growth in milk production quantity during the 2010-2018 period was: India - 8.238 million tons/year; USA - 1.401 million tons/year; China - 1.138 million tons/year[2], [3], [4].Additionally cattle provide large quantities of meat, the desired quality for which is highly placed and heavily regulated. Because of thesereasons the efficient breeding of dairy cattle requires strong measures for animal wellbeing support and preservation.

To overcome these challenges it is needed to gather, transfer and process information of importance from the farms in order to effectively monitor the whole cycle of breeding.This is impossible without the development and utilization of sensor networks, spread over huge areas.

Smart sensors are already in regular use in various fields like healthcare [5], smart cities, smart homes but also in mechatronics, robotics, autonomous enterprises and etc. Their application in the farming industry is an opportunity

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which will reduce necessary manpower and production losses.

AI and machine learning methods are capable of processingthe large quantities of data, provided by smart sensor networks, based on IoT devices [6], [7].

The goal of the presented work is to propose the structure of a system for diagnostics of specific diseases that dairy cattle suffer from - based on body temperature measurement and analysis of the collected data. The system is based on the IoT concept and cloud computing.The future development will be directed towards implementation of AI and Machine Learning methods for data analysis and classification in real time.

The paper is organized in the following sequence: section 2 describes the importance of the body temperature measurements for diagnosing diseases of critical importancein dairy cattle. The structure of a cloud based information system is proposed in section 3. Section 4 presents a field device for infrared temperature measurement using the IoT concept. Conclusions and future work are highlighted in the last section.

II. Body temperature measurement as a diagnostic approach in dairy cattle

Cattle suffer from numerous diseases, with the most often occurring, and economically impactful ones causing body temperature deviations.

Based on the work of Kelton et al. [8], Table 1 presents a list of the most severe and economically affecting illnesses which can be found in cattle; their occurrence based on statistical analysis from different publication sources; the median of occurrence and the direction of resultant change in average body temperature. Disease occurrence is typically described as Lactation incidence rate (LIR) within dairy cattle.

Disease	Occurrence	Median	Body temperature change
Milk Fever	0.03 % - 22.3 %	6.5 %	↓
Ketosis	1.3 % - 18.3 %	4.8 %	↓
Mastitis	1.7 % - 54.6 %	14.2 %	↑
Metritis	2.2 % - 37.3 %	10.1 %	↑
Displaced abomasum	0.3 % - 6.3 %	1.7 %	↑

Table 1.Cattle disease occurrence and resultant body temperature deviations

The average body temperature of a healthy Holstein cattle is 39.16 ºC; σ = ±0.19 ºC[9].With temperatures above 39.5ºC and bellow 38.5ºC being indicative of an illness.

One of the most commonly found diseases in dairy cows and which has a powerful impact on the cattle industry is mastitis[9]. It causes subsequent core body temperature spikes in the range 40.87ºC - 42.10ºC throughout the day. Its effects are related to spoilt milk quality, high treatment costs, decreased longevity and increased livestock culling. The temperature spikes of $\Delta T_{MIN} = 1.71$ºCcreate a potential opportunity for early detection of this disease, which as a result will prevent the animals from udder health deterioration and will improve the possibilities for efficient treatment.

Cattle suffer from additional infectious diseases such as bovine respiratory disease complex (BRDc), BVD virus and Johne's disease[10]. These diseases possess high infectious rates among herds, their detection is difficult via conventional methods due to the initial asymptomatic behavior of infected animals and have major financial impacts[11].

These common diseases can be detected using body temperature measurements. For it to be applied, this diagnostic approach requires enhanced accuracy and stability of the measurement [9]. One acceptable method is the use of a rectal thermometer. The obtained information is often correlated with the deep body temperature.The disadvantages of this method are the necessity of operator engagement and oversight, which leads to a scalability limitation and it is also stressful for the animals.

Another approach to collect valid data for the deep body temperature is the use of ingestible bio-sensors, placed within the rumen of the cow which transmit the measurement samples via a wireless communication link (LoRa, BLE or NBIoT). The obtained data is strongly correlated with those from the rectal measurement, so they can be considered as indicative for the deep body temperature.This approach is less invasive than the rectal measurement and suitable for automation. It is relatively difficult to construct the sensor in order for it to be secured from the gastric fluid and pressure in the rumen and also to not hurt the animal during the exploitation cycle [9].

Infrared thermography (IRT) is another diagnostic approach for monitoring cattle health. It is also a non-invasive, distant, and passive method for temperature measurement and it is appropriate for automation. In [6] the correlation between the temperature values of the eye and deeply inside the body is discussed. There it is suggested that the lacrimal caruncle region of the eye can conduct the deep body temperature and that they are strongly correlated. Thus measuring the eye temperature by infrared thermography means provides information for the body temperature. The disadvantage of this method is the complexity of measured data processing in order to obtain valid results, which match the deep body temperature. This is due to many factors - distance to the radiating surface, solar loading and wind speed. Additionally implementing a high resolution IR camera is expensive and requires a specially trained operator to handle, thus eliminating the mass scalability of such a system and limiting its applicability and adoption purely within scientific research.

The proposed work aims to present a system which has several advantages over currently implemented ones: it is of lower complexity and cost than the typical utilization of high-definition IR cameras, while still allowing applicability of state of the art thermographic analytical methods and 2-D signal processing algorithms; the system does not require each animal to be fitted with an individual thermal monitoring device, which enables a more centralized organization to be implemented within farms, compared to distributed Wireless Sensor Node (WSN) systems; the temperature from different areas of the animal's body can be monitored, not only the internal rumen temperature, which gives opportunities for more sophisticated zone-based thermal correlation analyses to be performed.

Within the following chapters the functional dependence of the measured IR temperature from the distance was modeled on the basis of performed measurements and a method for the effect's compensation is presented. Wind speed correlation can be modeled by a simple linear equation and be easily compensated. Additionally a method for the reduction of solar loading effects is proposed.

III. Expected Benefits from the Implementation of IoT and Cloud Computing in the Diagnostics of Dairy Cattle

The term IoT spans over a large variety of application devices which utilize network-based communications. Currently such gadgets are so widely adopted in numerous areas that it appears that almost everything has this capability.

In general devices labeled as being IoT are all network based systems which participate in fields related to everyday life, which possess the preceding adjective "*smart*" - smart cities, smart transportation, smart homes, smart health and etc.

The IoT concept integration within the cattle industry is projected to contribute strongly towards the goal of real time acquisition of accurate animal status data while simultaneously reducing the necessary manpower. Thus the deployment of multiple cloud oriented services would be made feasible for monitoring the whole cattle life cycle, with on-field measurements being handled by intelligent edge-computing end-devices.

The collected information from various smart measuring units is processed in order to provide sufficient support for correct automated decision making and evaluation of the cattle health status. For this purpose deep learning algorithms in the local server or in the cloud can be applied [9]. A possible architecture of an IoT based information system for infrared temperature monitoring in a cattle farm is proposed in Fig. 3.It deploys the classic three layer IoT model with perception, network and application layers [12].

The perception layer contains the front-end devices, e.g. the measuring units. These devices consist of sensors, signal conditioning modules, data converters and an application processor. The front-end devices are intended to measure the body temperature of cattle and some additional parameters in order to obtain valid data.

The network layer conforms the IoT device-gathered information from the perception layer to standard telecommunication protocols. Next it transmits the newly formatted data to the application layer through the corresponding telecommunication network. Internet is the main network which performs the routing, information transmission, and control. In the network layer placed are also supplementary information centers and IoT management. Additionally this layer uses public and specific industrial communication networks.

The purpose of the application layer is to process the information sent by the network layer, and based on this data to perform real-time monitoring and troubleshooting of the IoT end-devices. It contains application infrastructure /middleware and multiple types of servers related to content, web and directory services. This Infrastructure/ middleware provides the IoT technology with computing, processing and resources. A very important characteristic of the application layer is that it ensures information sharing and security. The development of this layer is aimed towards providing much richer datasets. These applications determine the format type, the volume of the required data from the sensors, and the frequency of acquisition.

Currently two Machine Learning based models are under development and their performance is being evaluated:

• Softmax Regression model, employing Elastic net regularization, trained via Mini Batch Gradient Descent and implementing Simulated Annealing and Early Stopping;

• Deep Neural Network model, employing He initialization, ReLU activation function, Batch normalization, Dropout regularization and an ADAM optimizer;

The data set, which is used to train these ML models consists of: the IR imaging data with applied kernel-based

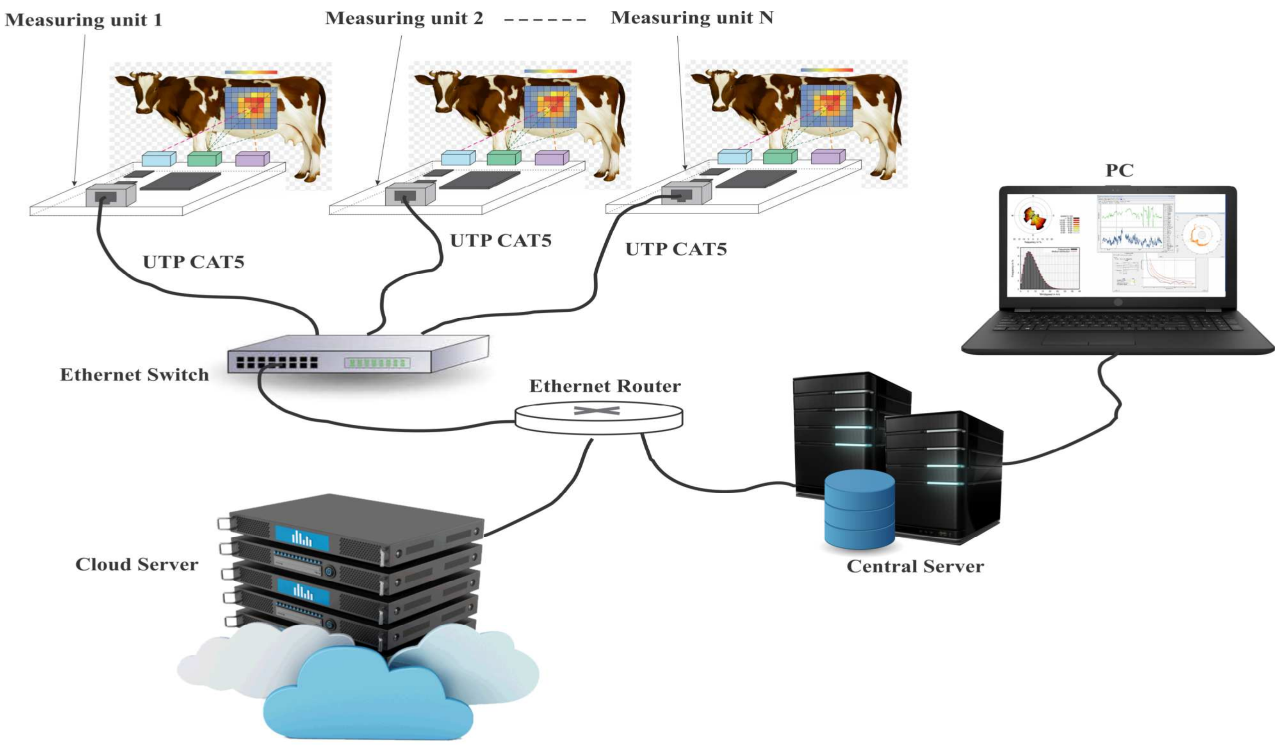


Fig. 3. IoT based cattle monitoring system using infrared thermography

median filtering, which removes spurious thermal pixel peaks in the image, uncorrelated in value with the surrounding pixels; sun position and wind direction sensor data. The main challenges towards the development of a proper ML model are: the necessitated acquisition of large amounts of real training and testing data, due to the fact that application of Data Augmentation techniques is typically not suitable and not recommended for biomedical AI systems; the choice of the most accurate ML classification algorithm and implementation of fine tuning to the model.

IV. Design of IoT based device for real time temperature measurement in dairy cattle

Each front-end measuring unit has a fixed position placed on a supporting frame within the cattle farm. The positioning of the device is dependent on the necessity to perform thermographic imaging of a specific area of the animal's body. Infrared heat radiation in the eye area (the so-called lacrimal caruncle area) has been found to be directly correlated with changes in the animal's body temperature [11]. The thermographic analysis performed by the developed measuring system is based on the use of a simple 8x8 matrix infrared sensor and a distance sensor.

A. Description of the functional blocks

The structure of the device can be split into four main blocks - microprocessor, sensors, communications and power supply. Fig. 4 presents a block diagram of the developed system. The functions of each block are as follows:

•Microprocessor block

-Establishes a communication with the Sensor block;

-Analyzes the raw data and performs mathematical image processing;

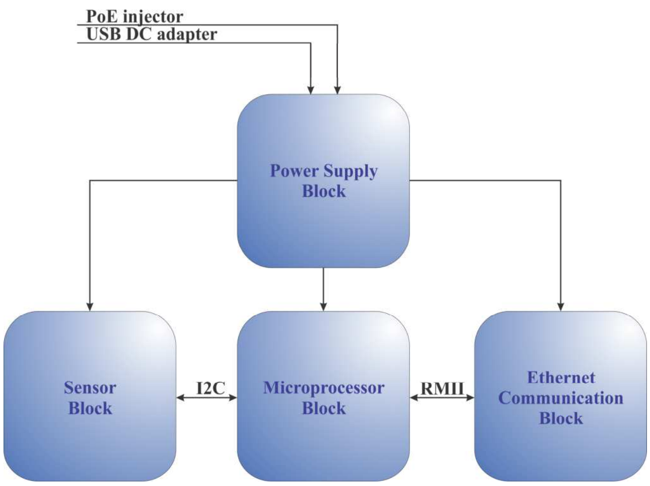


Fig. 4. Block diagram of the developed system

- Packages images and adds control information (checksum, CRC, timestamp, SHA identifier, etc.);

-Establishes an interface connection with the Ethernet communication block based on SPI;

-Transmits thermographic images to the local server.

For this purpose the STM32F105RCT6 microcontroller from STMicroelectronicshas been chosen. It is powerful enough to perform digital processing of the measured data and can operate as an edge computing node.

•Sensor block

- Captures thermographic matrix images;

- Measures the distance to the analyzed object with a high accuracy;

- Establishes a communication with the Microprocessor block based on a I^2C interface connection;

- Transmits raw sensor data to the Microprocessor block.

The block contains: matrix IR sensor AMG8833; ToF distance measuring sensor VL53L1; NTC thermistor - NCP15XH103F03RC.The implementation of the sensors is shown in Fig. 5.

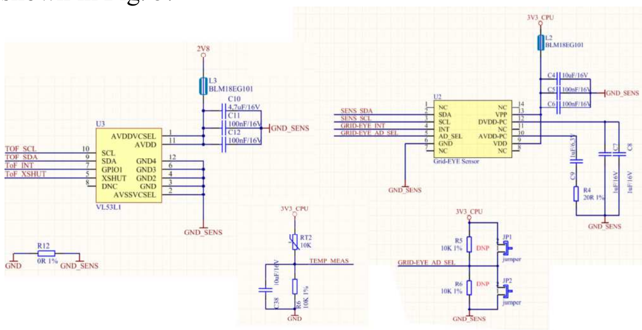


Fig. 5. The sensors and their interfacing to the microprocessor block

The matrix IR sensor AMG8833 was selected for the specific application. It allows the capture of a thermographic image with a resolution of 8x8 pixels. Due to its structural features, the relative absolute temperature measurement accuracy of matrix sensors is very limited and does not exceed ±1°C in all modern IR sensors of this type. The main parameters of the chosen sensor are:

•Range: 0°C - 80°C;

•Absolute accuracy within the range: ±2.5°C;

•Sensor resolution: 12 bits; 1LSB = 0.25°C;

•NETD: ±0.05°C.

The NETD parameter is indicative of the accuracy of the sensor in determining the super-dynamic difference between the readings of two separate pixels, part of the infrared image. Precisely because of the sensor's ability to accurately determine temperature differences - a system of such type that monitors the time-varying body temperature of the animal is able to detect the manifestation of disease, which leads to a significant change in the daily thermal profile.

There is a functional dependence between the actual temperature of the object and the camera-object distance. In order to measure the distance from the object to the monitoring system the VL53L1 ToF sensor was added, which has the following parameters:

•Distance measuring range: 0-90cm;

•Absolute accuracy in the measuring range: ±1%.

•Ethernet communication block

- Implements the physical layer and MAC layer of the Internet protocol stack;

- Transmits data in duplex mode with transfer speed 100Mbps.

The block is based on the integrated circuit W5500 of Wiznet which contains built-in Ethernet PHY (physical) and MAC (link) hardware modules. Also it provides a software implementation of the TCP/IP stack for communication between Ethernet devices.

•**Power supply block** based on PoE technology, with peripheral switching and linear mode voltage regulators.

Fig.6 shows a photograph of the constructed edge-computing sensor module.

B. Experimental results

In order to evaluate the functional correlation between the object distance and the measured IR temperature - tests were performed using an absolute black body Fluke Calibration 4180, MLX90614 IR point sensor and VL53L1 ToF sensor. Eq. 1 was derived via a regression mathematical model, constructed based on the performed measurements, with the result being a model-defined compensation component ΔT, which needs to be added to the measured IR value. Implementation of this compensation method was shown to drastically improve measurement accuracy for distances up to 32cm.

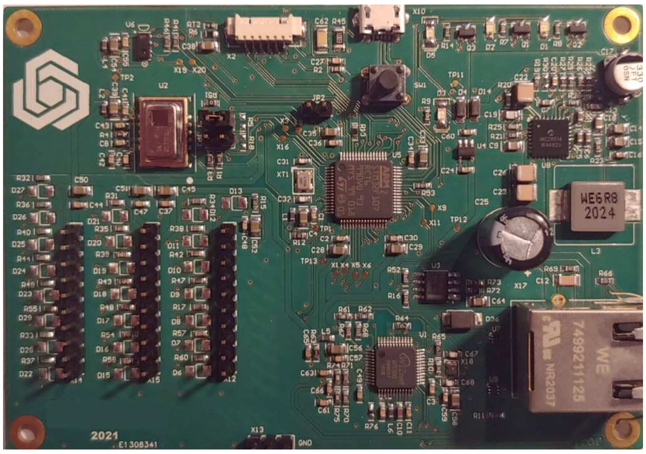


Fig. 6. Constructed edge-computing sensor module

$$\Delta T = 51.4 - (3.27 * T_{MEAS}) - (0.596 * D_{MEAS}) + (0.053 * T_{MEAS}^2) - (0.002025 * D_{MEAS}^2) + (0.02623 * T_{MEAS} * D_{MEAS}) \quad (1)$$

When performing IR measurements special focusing lenses have to be used - typically these optical systems are constructed from materials such as: saphire, ZnSe, KCl, KRS-5 and CdTe. Incident object reflected sunlight causes spikes in the MWIR (mid-wave infrared) band of 3µm-5µm resulting in image interference. This sunlight loading effect can be compensated by - implementing multiband IR measurement with utilization of linear narrow bandpass filters; multi-sensor thermal image capturing with planar distance-deviated field of views (FoV).

In order to determine the accuracy of the designed measuring unit, conducted were experiments with a ThermaCam SC640 FLIR camera as a reference. The experimental studies were performed at an ambient operating temperature of 25.6°C, relative humidity of 48%.

The experimental study was performed by capturing two different types of objects:

Object A - black opaque tape with an emissivity of 0.985, laid on a heating plate, heated under the control of a PID controller to 38.8°C;

Object B - human palm, with human skin having an emissivity of 0.97, comparatively larger to cattle skin emissivity, which is 0.95.

The experimental results of the study of object A are shown in Fig.7 and for object B are depicted in Fig. 8.

Due to the comparatively smaller Field of View of the AMG8833 sensor than that of the FLIR camera, only the top left corner of Object A was shot, resulting in a difference between the FLIR maximum measured temperature point and the developed system maximum measured temperature value. The minimum measured temperature by the FLIR camera is 38.6°C, which is essentially the heating plate temperature. The average temperature of Object A was evaluated based on all pixels, part of image rows 2,3 and 4. This evaluated average value and the equivalent one for Object B were used to calculate a corrective value.

It can be seen from the image analysis that the measurement error of the developed system can be approximated as a constant offset in the positive direction. In order to calibrate the sensor, the value of this offset must be calculated and a corrective component must be formed. The corrective value was evaluated as to being 0.98°C.

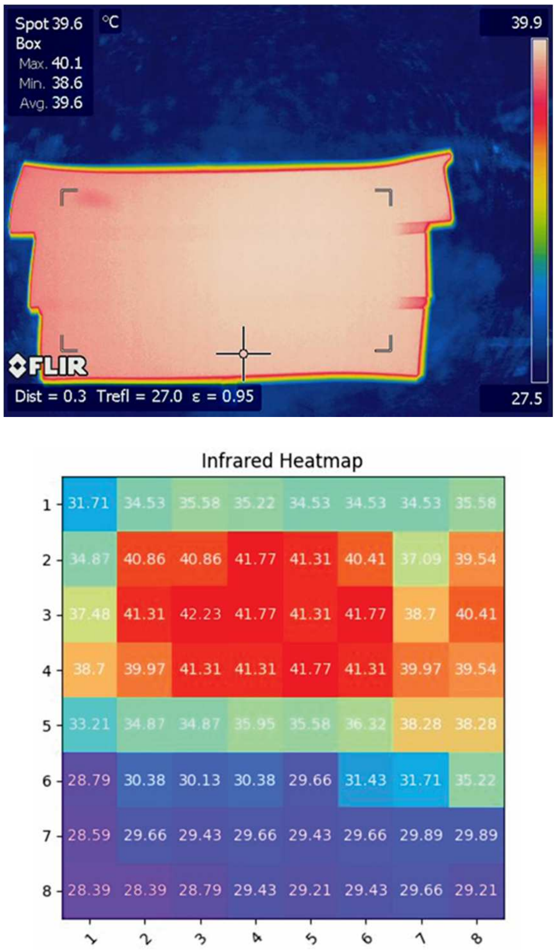
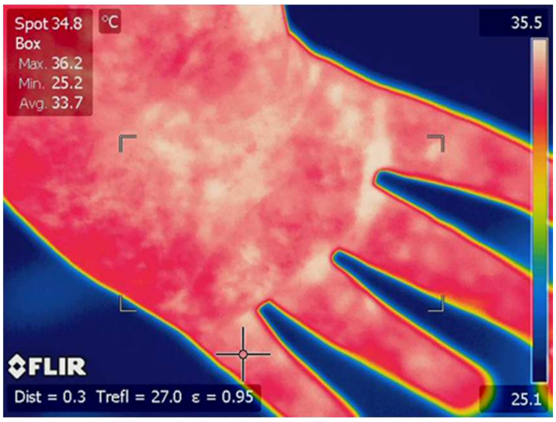


Fig. 7. IR images of object A taken by the FLIR camera (up) and by the designed device (down)



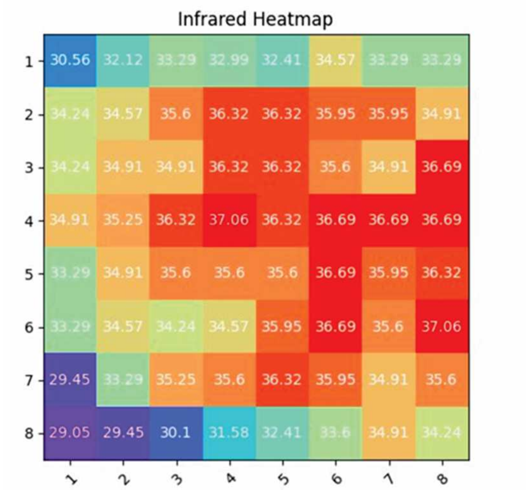


Fig. 8. IR images of object B taken by the FLIR camera (up) and by the designed device (down)

V. Conclusion

The paper presents an initial stage of the development of a complex system for dairy cattle temperature monitoring for diagnostic purposes. The overall architecture is proposed which is based on the application of IoT concept. Experimental studies of the front-end temperature measuring unit have been carried out. The verification of the results has shown the necessary accuracy. Further investigations will cover: eliminating the impact of sunlight loading and wind speed effects on the measurement accuracy; implementation of automated Deep Neural Network and Kernel-based disease detection and classification methods.

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