Available *online* at : http://jitce.fti.unand.ac.id/
JITCE (Journal of Information Technology and Computer Engineering)
| ISSN (Online) 2599-1663 |

A review of Image Processing Technique for Monitoring the Growth and Health of Cows

Zurnawita [1,2], Cipto Prabowo[3], Rahmadi Kunia [1], Ikhwana Elfitri[1]

[1] *Electrical Engineering Department, Universitas Andalas, Padang, West Sumatera, Indonesia*
[2]*Electrical Engineering Department, Politeknik Negeri Padang, Padang, West Sumatera, Indonesia*
[3]*Informations Technology Department, Politeknik Negeri Padang, Padang, West Sumatera, Indonesia*

ARTICLE INFORMATION

Received: February 3rd, 2023
Revised: March 8th, 2023
Available online: March 31st , 2023

KEYWORDS

CNN, regression, cattle, body weight estimation, computer vision,

CORRESPONDENCE

Phone: +62 812-6724-679
E-mail: zurnawita@pnp.ac.id

A B S T R A C T

In general, monitoring of animal growth and health is done directly by farmers (invasive measurement methods) which can cause cows to be injured or experience stress. To avoid this, several studies have been conducted on non-invasive methods using image processing technology. In this study, we systematically reviewed several works of literature to identify and synthesize published articles on image processing technology and image processing applications related to weight estimation and individual cattle identification. Analysis of image processing technologies used for weight estimation and individual cattle identification is the main objective of this article. Articles were searched through several databases and studies that met the inclusion criteria were analyzed and used in the review. The studies were divided into three main themes: image processing technologies, applications using image processing, and image processing research on cattle growth and health. It can be concluded that deep learning approaches are increasingly being studied, tested and considered as a viable and promising approach to monitor cattle weight and health in several aspects.

.

INTRODUCTION

Cattle are one of the animal protein-producing livestock that has increased in demand alongside other livestock due to global human population growth, rising incomes, and others, but due to climate change, a combination of traditional practices, socioeconomic differences, and environmental phenomena, livestock productivity has stagnated [1]. The current climate change causes drastic changes in temperature and humidity, this can cause problems especially in the growth and development of livestock cattle [2]. Monitoring cattle growth and development, which is often identified with real-time weight growth, is an important factor in cattle farming [3] [4], However, it is often ignored because it requires human resources and a lot of time so it is only done in certain conditions depending on the ability of human resources. Whereas cattle weight growth is closely related to health conditions.[5]. For example, young cattle should have good body weight development as it is related to the development of the immune system to keep the cattle healthy. It is important to be able to monitor and estimate cattle weights so that any deviations from growth can be optimally monitored so that the results can be used for management decisions, such as weaning and slaughtering [6].

Cattle detection and identification systems play an important role in cattle farming to reduce costs and workload [7]–[10]. Conventional image processing techniques combined with deep learning concepts are used to build a cattle detection and identification system. Knowing body weight by weighing is one way to monitor the growth and health of cattle in maintenance management. Conventional measurements are common but notoriously difficult because cows move around a lot, causing stress and taking a long time.[11]. This makes the use of traditional physical weighing methods inefficient. Another method is estimation using empirical relationships between morphological characteristics and body weight, by measuring chest circumference, height, hip height. However, the measurement of body dimensions is often time- consuming and can be detrimental to the performer if the procedure is not automated and handled properly. Nowadays, the use of computer technology equipped with sensors, cloud computing technology, the use of machine learning (ML) and artificial intelligence (AI) methods have changed many industries. They provide more benefits and are more efficient. So it is necessary to explore how

 Attribution-NonCommercial 4.0 International. Some rights reserved

advanced technology can help livestock farming, especially cattle farming [11]–[14]. Intelligent perception tools from various sensors on precision farms can obtain a large amount of data that can be used to analyze individual animals for better management and can potentially increase farm productivity.

METHOD

To learn more about computer vision and its implementation in the real world especially in the field of animal husbandry, which is the monitoring of the growth and development of cattle, researchers used the Systematic Mapping Study method by conducting several article reviews which were divided into 3 parts, namely technologies in image processing, applications that use image processing technology, and research related to the use of image processing technology in monitoring livestock growth and development.

The Latest Technology in Image Processing

Image Acquisition

The initial phase of image processing is the process of capturing or scanning an analogue image or non-image object into a digital image. Common technologies used in this phase include digital cameras, webcams, scanners, thermal cameras, digital microscopes, ultrasonography, Computed tomography (CT scan), Computed Radiography, Magnetic Resonance Imaging, Mammogram or other sensors. From these devices, 2D information is produced which is often described as a 2D function f(x,y) that represents the width and height of the image, such as an RGB image with each coordinate (x,y) has an RGB value that determines the pixel value or depth of the image, for example if at point x,y has an RGB value of (255,255,255) which is declared as white or (0,0,0) which is declared as black then at that point is declared to have no information. The quality of the resulting image is highly dependent on the stability of the illumination, the distance between the device and the object and the resolution of the device. In addition to 2D information in the data acquisition process can also produce 3D information that can be done in 2 ways, namely active techniques and passive techniques. Active techniques are carried out with structured lighting, the devices used are 3D cameras, RGB-D, LiDar and others, while passive techniques are carried out by taking objects in various positions. 3D information is described by a function f(x,y,z) with width, height and depth information.

One of the uses of image processing in industry is the detection of product defects, which is often referred to as machine vision. The reliability of this machine lies in the excellent quality of lighting and image acquisition tools that fulfil the prerequisites in order to produce very high image quality as shown in Figure 1 [15].

It can be concluded that the utilization of the device for data acquisition depends on the object to be captured, the environmental conditions around the object, and the distance between the device and the object.

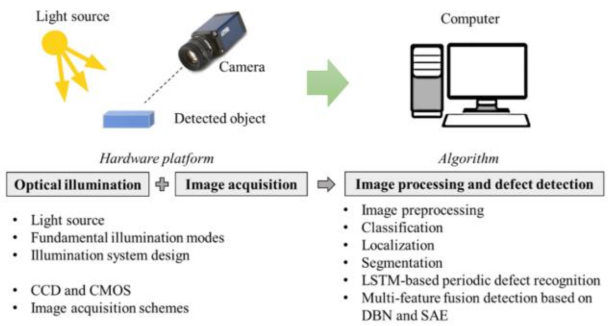

Figure 1. Visual Inspection System Architecture in Industry [15].

Image Enhancement

In some practical image processing applications facing poor image quality such as underwater applications that must overcome blurred image quality, lack of lighting, low contrast and others so that the image quality improvement process is needed with the retinex method which will produce better image contrast quality from the original image.[16], [17].

In some implementations, the image quality may be caused due to the influence of the sensor installation, resulting in the contrast between the background and the target in the image being low and the edges being blurred. In addition, the large distance between the target and the sensor at the scene may cause obvious noise in the image due to the influence of atmospheric thermal radiation, so the texture information of the target is not prominent enough, resulting in poor image visual effects. Some traditional techniques such as the use of gaussian filters to smooth one-dimensional signals as an improvement in the quality of edge detection. The use of histogram equalization can be used to improve the contrast and brightness of images used in image defogging, medical image processing, and target detection.

Gauss gradient determines the gradient/descent of 2D scalar images and 3D volumes using the derivative of the Gaussian approximation. The 2-Dimensional representation of the Gaussian kernel is as follows:

$$h(x,y) = \frac{1}{2\pi\sigma^2} e^{-(\frac{x^2+y^2}{\sigma^2})} \quad (1)$$

Where: σ = smooth scale
In general, the function is written as follows:

$$f(x,y) = g(x)h(y) \quad (2)$$

Gradient measurements along x and y can be separated by 2 filtering and Gaussian functions can be separated and decomposed using 2 1D Gaussian functions.

$$f(x,y) = \left(\frac{1}{2\pi\sigma^2} e^{-\frac{x^2}{\sigma^2}}\right)\left(\frac{1}{2\pi\sigma^2} e^{-\frac{y^2}{\sigma^2}}\right) \quad (3)$$

An important property of a Gaussian filter if it satisfies

$$\Delta x \cdot \Delta w \geq 0.5 \quad (4)$$

Δx and Δw are the spatial and frequency variances, respectively domains.

The input image can be either a grayscale or a color image as shown in Figure 2. The term σ (sigma) is used to define the Gaussian kernel in both directions. A higher sigma value will result in a blurred output. Choose a sigma value that suits the gauss gradient edge detection approach.

$$g(x) = \left(\frac{1}{2\pi\sigma^2} e^{-\frac{x^2}{\sigma^2}}\right) \quad (5)$$

Gaussian kernels are generated along the x direction and y direction. The resulting Gaussian kernel involves the convolution of the Gaussian function and the first-order derivative of the Gaussian function.

$$g'(x) = -x\left(\frac{1}{\sigma\sqrt{2\pi}}\right)\frac{e^{-x^2}}{2\sigma^2} * \frac{1}{\sigma^2}) \quad (6)$$

$$g'(x) = -x * g(x) * \sigma^2 \quad (7)$$

Then the representation of the Gaussian Kernel along the x and y directions is as follows:

$$H(x) = g(x) * g'(x) \quad (8)$$

$$Hy = Hx' \quad (9)$$

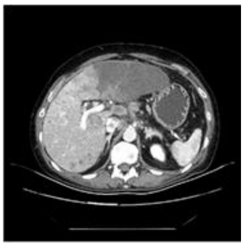

Figure 2. Medical Image Input

Gaussian smoothing is performed on the image using the resulting kernel and the result is depicted as shown in Figure 3.

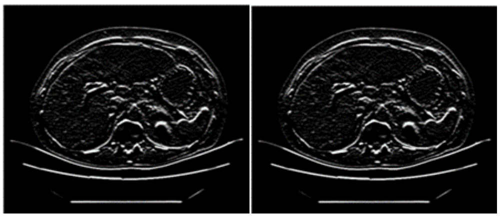

Figure 3. Gaussian smoothing results along x and y directions

The resulting edge detection fulfils the following formula:
Edge output = abs (Gx) + abs (Gy) (10)

With pictures as shown in Figure 4.

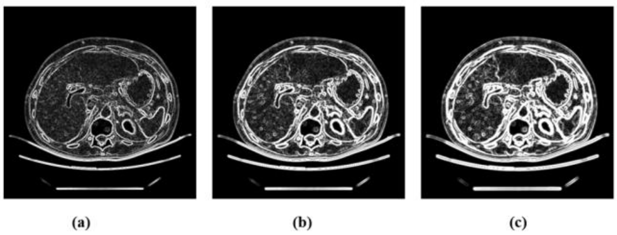

Figure 4. Edge detection with Gauss gradient output for σ= 1,1.5, 2.

The application of several methods in image quality improvement is possible such as image quality improvement Dance movement applies multiscale convolution is used for image pre-processing, then to enhances the edge detection operator using the traditional Laplace method combined with Gauss filter. The use of Gaussian Filter is to smooth the image and suppress noise, then a Laplace gradient edge detector is used to process the edge detection. The image details extracted by the Gauss-Laplace operator increase the brightness of the image with linearly converging weights thus reconstructing an image with clear edge details and strong contrast [16].

The use of improper methods in image enhancement operations can cause the main object to be biased so as to eliminate the details of the real object, therefore it is necessary to try several existing methods in image enhancement which are strongly influenced by the environment around the object.

Image Restoration

In the development of the camera and smartphone industry, solving the classic problem of image recovery, namely the removal of unwanted degradation such as noise, blur, rain and so on, continues to develop mostly based on ConvNets, which achieves impressive results but shows limitations in remote image retrieval. One way to overcome the problem is by using a transformer method with a self-attention layer on a low-resolution feature map.

The backscatter estimation algorithm can enhance the contrast and remove the color aberration of light absorption in underwater images that often suffer from blurring and color degradation.[18]. The use of image restoration should not change the features and size of the object but the use of the wrong technique can negatively affect the image quality of the object.

Color Image Processing

The use of binary image processing technology and grayscale-based images in the process of measuring the quality of asphalt mixtures is strongly influenced by the quality of lighting. Strong lighting will cause the asphalt to be more shiny, leading to a decrease in the calculated layer ratio. Vice versa, overestimation of the layer ratio can be caused due to poor lighting conditions causing stripped areas to be represented by dark pixels. The use of the method of averaging the luminance of digital images as an indicator can quantify the degree of stripping in the measurement of asphalt mix quality caused by moisture [19].

Wavelets And Multi-Resolution Processing

A multi-resolution approach using contour transform and wavelet transform to combine CT and MRI images in an effort to improve image quality results in pixel clarity and retains information at the corners and edges of the fused image without losing data so that the information can help doctors in better clinical diagnosis of brain diseases [20].

Image Compression

As many images are generated in everyday life, the challenge is the storage and transmission of image data which sometimes in the implementation of the application requires image data with small data size but still has high fidelity so that several studies related to lossless compression algorithms are developed. Combining linear prediction, integer wavelet transform and Huffman coding can produce compression from 6.22% to 72.36% [21].

 https://doi.org/10.25077/jitce.7.01.8-18.2023

Morphological Processing

Morphological operations are image processing techniques that are based on the shape of segments or regions in the image. These operations include: boundary/contour search, dilation, erosion, closing, opening, and filling. Morphological operations used can help improve the quality of damaged images. The use of morphological operations and binary logical processes in vehicle detection and vehicle speed detection systems produces satisfactory results that help to reduce the number of accidents [22].

Segmentation Procedure

The division of homogeneous regions in an image can be done by image segmentation. Converting an input image into an output image based on the attributes of the extracted image can be named as segmentation. Segmentation can also be used to distinguish objects and backgrounds by dividing the image into its own intensity regions.. The algorithm of image segmentation is divided into two types, namely:

1. Discontinuity
   The division of images based on differences in intensity, such as points, lines, and edges.
2. Similarities
   Image division based on the similarity of criteria, such as thresholding, region growing, region splitting, and region merging.

Automatic evaluation of medical images is widely used for screening. The use of segmentation of extracted leucocyte sections from thin blood smear images using the CNN method with VGG-UNET architecture produces good performance with an accuracy rate of up to 97% [23].

Object Detection and Recognition

Handwriting is still widely used in general so it is still interesting to analyze it to get information in the future. Handwriting recognition is a big challenge due to the diverse and overlapping writing patterns. Most studies use lexicon- based methods that require a large number of data samples up to 50 K samples to get good results. The use of the lexicon-free YOLO v3 method obtained good results even though it only used 1200-word samples with an error rate of up to 29% for word recognition and 9% for character recognition [24].

Application Of Image Processing Technology

Face Detection

Artificial neural networks are widely used in several object detection applications. Artificial neural networks have a data learning feature function known as a black box, but it has a less strong interpretability to give users knowledge about how the model can obtain results and how to improve the capabilities of the model. Whereas fuzzy systems have good interpretability by defining fuzzy rules based on experts but have the disadvantage of being less flexible in adapting to differences in a set of data and require large rules to get better accuracy when facing data sets in high dimensions and will even cause rule explosion.

The application of neuro-fuzzy which is a combination of artificial neural network models with fuzzy systems has been carried out in several domains. The main problem that often arises is that parameter optimization takes a long time and the next problem is that there are few innovations in fuzzy methods for feature extraction while the Cycle Reinforce Hierarchical Model (CRHM) can be used as an effective and efficient recognition. CRHM consists of a hierarchical structure, a group of fuzzy subsystems, and a cycling mechanism. The construction of a hierarchical structure is used for feature extraction and converting low-level features into semantically advanced features. The adoption of a group of fuzzy subsystems as feature extraction units in each hidden layer ensures feature diversity, and is useful for avoiding fuzzy rule explosion, thus reducing the time for clustering. In the first cycle, it is used to connect the hierarchical structure and the output layer directly and then transfer the set parameters continuously to strengthen the features gradually. The CHRM method produces higher recognition rate than CNN with faster training time [25].

The use of an artificial neural network on deep learning method for face sketch synthesis with the application of an architecture containing two convolution layers, a pooling layer, and a multilayer convolutional perceptron layer is used to learn the mapping from face photos to sketches. In this method, there is no need to solve complex optimization problems, but only calculate convolution and pooling operations, thus improving the synthesis efficiency. Another advantage is that the global feature extraction of the convolution layer can produce more continuous and fixed facial contours [26].

A face recognition system that applies a combination of Principal Component Analysis (PCA), K-Means clustering, and Convolutional Neural Network (CNN) methods can produce a smaller network that reduces training time, eliminates redundancy, and maintains variance with a smaller number of coefficients. Then the use of a K-Means clustering model trained using compressed PCA can produce data that selects K-Means clustering centers with better characteristics that serve as the initial values of the CNN and act as input data. The use of this method results in more efficient face identification compared to other Face Recognition (FR) techniques namely PCA, Support Vector Machine (SVM), and K-Nearest Neighbor (kNN)[27].

Object Classification

The application of Coarse-to-Fine Pseudo Supervision-guided Meta-Learning (C2FPS-ML) for unsupervised multiple-shot object classification is used to solve target tasks that have few labeled examples with additional unlabeled datasets. The method acquires prior knowledge from the additional unlabeled dataset during unsupervised meta-training. It then uses the prior knowledge to assist downstream multi-shot classification tasks. Optimization of the meta-task sampling process at the unsupervised meta-training stage using the Coarse to Fine Pseudo Supervision method in C2FPS-ML which is the dominant factor to improve the performance of meta-learning-based FSL algorithms. Learning new concepts in a progressive or hierarchical manner following the coarsest to finest way can use human behavior simulation as a development step of the C2FPS-ML method [28], [29], [30].

Object Detection

In the implementation of object detection [31] [32]– [34], there are two technical challenges, namely accuracy, and speed. Several recent anchor-free detection studies have achieved high performance, but are very difficult to implement in the real world due to model complexity and slow speed. Combining Cross-context Attention Mechanism (CCAM), Receptive Field Attention Mechanism (RFAM), and Semantic Fusion Attention Mechanism (SFAM) can balance accuracy and speed with an attention-guided mechanism to highlight the interaction of object synergy regions, and suppress non-object synergy regions. The construction of a novel attention mechanism that considers channel, spatial, cross-context, and neighborhood context information simultaneously improves the Average Precision (AP) metric in small object detection [35].

Current Research on Image Processing Application for Livestock Growth and Development

Livestock Health

Monitoring livestock behavior is critical to understanding livestock welfare and health status. [36] [37], [38]. The common method is invasive by direct observation and direct measurement of the cow's body, which is not efficient and effective because farmers must provide time and special equipment to monitor and cannot be done continuously [39]. One of the most powerful monitoring methods is a non- invasive monitoring system that uses infrared light or a thermal camera to measure the body temperature of cows in the area between the eyes (forehead).[40] in addition to the vulva of the cow [39] because changes in temperature in this area are one of the main factors in changes in health conditions. The need for more precise farming, monitoring cow health is not only on the temperature factor but also the overall activities involving cows, namely cow nutrition [41], cow environment[42], cow behavior [43][44], cow behavior changes in cow weight [45] and others. Commonly used methods are Convolutional Neural Networks (CNNs) [46], Long Short-Term Memory (LSTM) [47], Mask-Region Based Convolutional Neural Networks (Mask-RCNN)[48], and Faster-RCNN[49], [50]

Body Score Condition

Cattle body measurement [51][10][37] is an important task in precision animal husbandry, as weight changes can be categorized as health changes in cattle. One measurement of cattle body is by using Body Condition Score with rank 1-5, with 1 being too thin and 5 being too fat. [52] (65). This was previously done manually by touching or looking at the back (spine or top line), short ribs, hip bones (hook and pin) and tail head.[53], [54]. But to do that requires an expert. Image processing technology is an option for body condition scoring observation nowadays as shown in Figure 5 [55].

Body condition assessment with image processing technology is based on the feature extraction model analysis assessment method by extracting body surface geometric features related to body condition (animal body contour, shape, etc.) [55], [56]. Non-contact body measurement methods using 2D [11]as well as 3D or RGB-D cameras [54], [57]. Using 3D data to build geometric features for body measurement is prone to errors because 3D cameras require good lighting and are light-sensitive and slow in image processing.[58], [59]. In 2D camera image capture, the use of the Single Shoot Multi Box Detector (SSD) method can improve classification accuracy and location accuracy in tail detection and evaluate BCS. However, capturing with a 2D camera has the disadvantage of not having information about the depth of the tail.

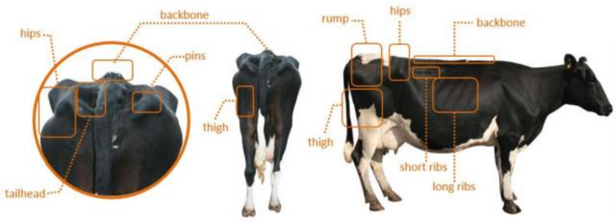

Figure 5. Body Condition Score Access Area [55]

In the determination of BCS, feature extraction of the chest circumference is required, with the use of RGB-D cameras that produce depth information and the use of the Deeplabcut method with Resnet architecture achieving relatively high performance.[60]. The use of CNN in BCS determination can also improve classification accuracy and location accuracy, especially when using Faster R CNN [50], [60], [61].

Weight Estimation

Cow feature extraction using SOLO application [48] application and the discrete curvature calculation method to extract the cow's body size to calculate feature points.[62] extract the size of the cow's body to calculate feature points. and calculate the cow's body size parameters with the Euclidean distance calculation method [63] can be used to visually see the growth and development of cows [64]. Prediction of cow weight to determine the weight of cows automatically using the Artificial Selected Weighting Method which compares manual data collection and uses image processing technology with steps as shown in Figure 6 [65].

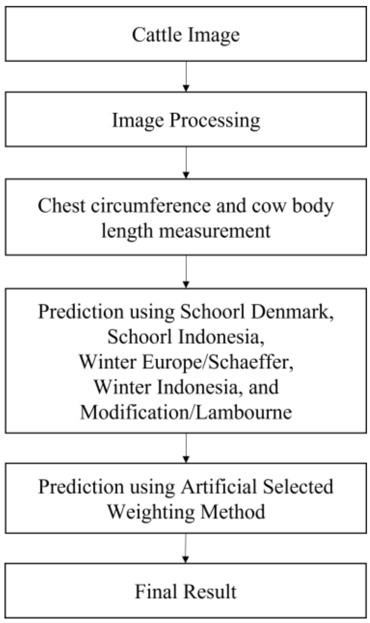

Figure 6. Research design

 https://doi.org/10.25077/jitce.7.01.8-18.2023

Some formulas for predicting cow weight are:

Schoorl Denmark:

$$W = \frac{(LD+22)^2}{100} \tag{10}$$

Schoorl Indonesia:

$$W = \frac{(LD+18)^2}{100} \tag{11}$$

Winter Europe / Schaeffer's Formulas:

$$W = \frac{PB \times (2{,}53 \times LD)^2}{300} \tag{12}$$

Winter Indonesia:

$$W = \frac{PB \times (LD)^2}{10815.15} \tag{13}$$

Modification / Lambourne Formulas:

$$BB = \frac{(LD)^2 x PB}{10840} \tag{14}$$

Where:

PB = Cow Body Length
LD = Cow Body Circumference

Manually, the cow's circumference can be thought of as the base area and the body length as the height. The chest circumference is obtained by winding a string behind the gumba through the back of the shoulder blades. Meanwhile, body length is measured from the shoulder to the protrusion of the sitting bone, compared to the measurement in the image data. The difference in measurement results produced is still in a reasonable category because it is greatly influenced by many factors such as the environment, stress levels and others. Even manual weighing done by stressing the cow can reduce the weight by 5-10% [65].

Cow Individual Recognition

Identification of cattle [66] is indispensable for the purposes of disease prevention and control, breeding agencies. Feed quality traceability and others. The use of traditional identification methods such as the use of ear marks and tattoos on the skin of cattle is less efficient and hurts cattle [67]. Non-invasive identification using cameras is an option because it is effective and cost-effective. Several methods have been applied such as ear marker recognition [68]. This method has the disadvantage that if the marker is covered by the cow's ear, the system cannot detect it. The next method is based on muzzle point matching, this method requires a high-resolution camera and the system cannot detect it [69]. This method requires a high-resolution camera and a very close distance to the object so that implementation in the field will be very difficult. Another method is by cow face recognition, this method takes part of the cow's face from the horns to the cow's muzzle as shown in the Figure 7. The use of the YOLO application [70] application that is commonly used for human face recognition is quite effective in detecting individual cow faces but if the face position is sideways or downward it will result in false detection [66] [46]. The fusion of human face recognition methods namely ArcFace Loss [71] and Retina Face [72] mobilenet [73] produces high performance with a faster computation rate, but the use of this application produces maximum performance only in offline conditions [67].

Figure 7. Cow face area

Automatic cattle image recognition is a necessity for government agencies responsible for this activity or farmers. Several studies have been conducted, including the use of Convolutional Neural Network methods to extract characteristics from cattle images and Support Vector Machines for classification. The accuracy of these methods achieved satisfactory results, comparable to other methods [10], [58], [74], [75].

The method of detecting anomalies in the continuous weight gain of cattle in the process of fattening cattle can be done with machine learning that applies several algorithms, namely the algorithms used are Decision Tree (DT), Gradient Boosting (GB), regression based on K-Nearest Neighbor (KNN), and Random Forest (RF) with the outlier detection process carried out to identify anomalous weight anomalies. Of the four algorithms, the DT model produced the best performance [59], [76]. Weight estimation using machine learning with Bayesian ridge algorithm through 3 stages namely segmentation, feature extraction and weight estimation on Korean cattle (hanwoo) produces good performance that produces efficient and lightweight models so that it can be used in embedded systems.[61]

Cow Behavior

Cattle behavior reflects the health, welfare, activity and production of cattle. Behavioral monitoring was initially done by direct observation but this became inefficient especially in precision farming conditions. Direct observation was replaced with inertial sensors [77]. But the position of these sensors sometimes changes or falls or runs out of resources so that monitoring is not efficient. The use of cameras is the next option using a combination of the C3D (Convolutional 3D) and ConvLSTM (ConvLSTM) network methods [78] and ConvLSTM (Convolutional Long Short-Term Memory) network methods to extract spation temporal features [79] to extract spatio-temporal features, and feeding the last feature to the softmax layer for behavioral classification can identify 5 behaviors namely feeding, exploring, grooming, walking and standing[80].

RESULTS AND DISCUSSION

In monitoring the growth and development of livestock using computer vision technology, choosing the right type of camera is very important to get maximum results. RGB cameras are suitable for monitoring activity and obtaining physical details of animals at an affordable price, but are less effective in low lighting conditions. Thermal cameras are excellent for monitoring animal body temperature and do not affect animal stress, but they are relatively expensive and sensitive to lighting conditions. Depth sensor cameras are ideal for acquiring information on the depth of objects and body shape of animals, but they are also expensive and sensitive to camera position and distance. Therefore, camera selection should be tailored to the monitoring needs and purpose as well as the surrounding environmental conditions.

In addition, special attention should also be paid to the factors of camera position and distance, camera resolution, and lighting conditions that may affect the quality of the resulting images. The use of stereo camera techniques can improve image quality by providing additional information about the shape of objects, but still requires attention to these factors. By paying attention to these factors, the use of computer vision technology can help monitor livestock growth and development more effectively and efficiently.

Review results from various journals show that the use of image processing methods in monitoring the growth and development of livestock has produced positive results. Various image processing methods such as image enhancement, edge detection, segmentation, object recognition, and convolutional neural network (CNN) have been applied in monitoring the growth and development of livestock, especially cattle. In choosing the right image processing method, it is necessary to consider the needs and objectives of image processing as well as the characteristics of the image to be processed. In addition, the diversity of object data is very important to be used as training data for an algorithm used to account for variations in shape and size that can help improve accuracy. Various data augmentation techniques can be used to produce more varied and high-quality datasets.

The CNN method is the most popular method in monitoring livestock growth and development because it can produce accurate models in a relatively short time and can be applied to datasets with large sizes. Various CNN architectures such as AlexNet, VGGNet, and ResNet have been applied in monitoring livestock growth and development and have shown good results. Overall, the use of image processing methods and CNN can be an effective alternative in monitoring the growth and development of livestock, especially cattle. However, it should be noted that the accuracy of weight estimation or object detection depends on the quality of the image used and the diversity of object data used as training data

CONCLUSIONS

The use of image processing technology and the Convolutional Neural Network (CNN) method can be an effective alternative in monitoring the growth and development of livestock, especially cattle. In choosing the right camera for monitoring, it is necessary to consider the needs and objectives of monitoring as well as the surrounding environmental conditions. In addition, in choosing the right image processing method, it is necessary to consider the needs and objectives of image processing and the characteristics of the image to be processed. Diversity of object data is very important to be used as training data for algorithms to take into account variations in the shape and size of objects. Various data augmentation techniques can be used to produce more diverse and high-quality datasets.

CNN is the most popular method in monitoring livestock growth and development because it can produce accurate models in a relatively short time and can be applied to datasets with large sizes. Various CNN architectures such as AlexNet, VGGNet, and ResNet have been applied in monitoring livestock growth and development and have shown good results. However, it should be noted that the accuracy of weight estimation or object detection depends on the quality of the images used and the diversity of object data used as training data. Therefore, it is hoped that further research can be conducted to correct the shortcomings and develop this method so that it can be used more widely in the livestock industry.

ACKNOWLEDGMENT

I would like to thank the Director of Politeknik Negeri Padang and all friends who cannot be mentioned one by one who have helped in the completion of this article.

REFERENCES

[1] Directorate of Social Welfare Statistics, Consumption of Calorie and Protein of Indonesia and Province, September 2021. BPS-Statistics Indonesia, 2021.

[2] W. S. Kim, J. Ghassemi Nejad, D. Q. Peng, Y. H. Jo, J. Kim, and H. G. Lee, “Effects of different protein levels on growth performance and stress parameters in beef calves under heat stress,” Sci Rep, vol. 12, no. 1, Dec. 2022, doi: 10.1038/s41598-022-09982-4.

[3] D. Singh, R. Singh, A. Gehlot, S. V. Akram, N. Priyadarshi, and B. Twala, “An Imperative Role of Digitalization in Monitoring Cattle Health for Sustainability,” Electronics (Switzerland), vol. 11, no. 17. MDPI, Sep. 01, 2022. doi: 10.3390/electronics11172702.

[4] Y. Wu, H. Guo, Z. Li, Q. Ma, Y. Zhao, and A. Pezzuolo, “Body Condition Score for Dairy Cows Method Based on Vision Transformer,” in 2021 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2021 - Proceedings, 2021, pp. 37–41. doi: 10.1109/MetroAgriFor52389.2021.9628437.

[5] C. C. Mar, T. T. Zin, I. Kobayashi, and Y. Horii, “A Hybrid Approach: Image Processing Techniques and Deep Learning Method for Cow Detection and Tracking System,” in LifeTech 2022 - 2022 IEEE 4th Global Conference on Life Sciences and Technologies, 2022, pp. 566–567. doi: 10.1109/LifeTech53646.2022.9754915.

[6] Y. Qiao et al., “Intelligent perception for cattle monitoring: A review for cattle identification, body condition score evaluation, and weight estimation,” Computers and Electronics in Agriculture, vol. 185. Elsevier B.V., Jun. 01, 2021. doi: 10.1016/j.compag.2021.106143.

[7] Y. Wu, H. Guo, Z. Li, Q. Ma, Y. Zhao, and A. Pezzuolo, “Body Condition Score for Dairy Cows Method Based on Vision Transformer,” in 2021 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2021 - Proceedings, 2021, pp. 37–41. doi: 10.1109/MetroAgriFor52389.2021.9628437.

[8] R. Garcia, J. Aguilar, M. Toro, and M. Jimenez, “Weight-Identification Model of Cattle Using Machine-Learning Techniques for Anomaly Detection,” in 2021 IEEE Symposium Series on Computational Intelligence, SSCI 2021 - Proceedings, 2021. doi: 10.1109/SSCI50451.2021.9659840.

[9] L. Anifah and Haryanto, “Decision Support System Cattle Weight Prediction using Artificial Selected Weighting Method,” in Proceeding - 2020 3rd International Conference on Vocational Education and Electrical Engineering: Strengthening the framework of Society 5.0 through Innovations in Education, Electrical, Engineering and Informatics Engineering, ICVEE 2020, Oct. 2020. doi: 10.1109/ICVEE50212.2020.9243263.

[10] Mikel Gjergji et al., “Deep Learning Techniques for Beef Cattle BodyWeight Prediction,” in International Joint Conference on Neural Networks (IJCNN), 2020.

[11] Y. Wu, H. Guo, Z. Li, Q. Ma, Y. Zhao, and A. Pezzuolo, “Body Condition Score for Dairy Cows Method Based on Vision Transformer,” in 2021 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2021 - Proceedings, 2021, pp. 37–41. doi: 10.1109/MetroAgriFor52389.2021.9628437.

[12] T. T. Zin, “An Automatic Estimation of Dairy Cow Body Condition Score Using Analytic Geometric Image Features; An Automatic Estimation of Dairy Cow Body Condition Score Using Analytic Geometric Image Features,” 2018.

[13] K. K. Cevik, “Deep Learning Based Real-Time Body Condition Score Classification System,” IEEE Access, vol. 8, pp. 213950–213957, 2020, doi: 10.1109/ACCESS.2020.3040805.

[14] T. T. Z. Sosuke Imamura, Ikuo Kobayashi, and Yoichiro Horii, “Automatic Evaluation of Cow’s Body-Condition-Score Using 3D Camera,” in IEEE 6th Global Conference on Consumer Electronics (GCCE 2017), 2017.

[15] Z. Ren, F. Fang, N. Yan, and Y. Wu, “State of the Art in Defect Detection Based on Machine Vision,” International Journal of Precision Engineering and Manufacturing - Green Technology, vol. 9, no. 2. Korean Society for Precision Engineeing, pp. 661–691, Mar. 01, 2022. doi: 10.1007/s40684-021-00343-6.

[16] D. Shen, X. Jiang, and L. Teng, “A novel Gauss-Laplace operator based on multi-scale convolution for dance motion image enhancement,” ICST Transactions on Scalable Information Systems, p. 172439, Jul. 2018, doi: 10.4108/eai.17-12-2021.172439.

[17] Y. Qi et al., “A Comprehensive Overview of Image Enhancement Techniques,” Archives of Computational Methods in Engineering, vol. 29, no. 1. Springer Science and Business Media B.V., pp. 583–607, Jan. 01, 2022. doi: 10.1007/s11831-021-09587-6.

[18] J. Zhou, T. Yang, W. Chu, and W. Zhang, “Underwater image restoration via backscatter pixel prior and color compensation,” Eng Appl Artif Intell, vol. 111, May 2022, doi: 10.1016/j.engappai.2022.104785.

[19] R. Xiao, P. Polaczyk, and B. Huang, “Measuring moisture damage of asphalt mixtures: The development of a new modified boiling test based on color image processing,” Measurement (Lond), vol. 190, Feb. 2022, doi: 10.1016/j.measurement.2022.110699.

[20] V. Bhavana and H. K. Krishnappa, “Multi-modal image fusion using contourlet and wavelet transforms: a multi-resolution approach,” Indonesian Journal of Electrical Engineering and Computer Science, vol. 28, no. 2, pp. 762–768, Nov. 2022, doi: 10.11591/ijeecs.v28.i2.pp762-768.

[21] X. Liu, P. An, Y. Chen, and X. Huang, “An improved lossless image compression algorithm based on Huffman coding,” Multimed Tools Appl, vol. 81, pp. 4781–4795, 2022, doi: 10.1007/s11042-021-11017-5#citeas.

[22] J. D. Trivedi, S. D. Mandalapu, and D. H. Dave, “Vision-based real-time vehicle detection and vehicle speed measurement using morphology and binary logical operation,” J Ind Inf Integr, vol. 27, May 2022, doi: 10.1016/j.jii.2021.100280.

[23] S. Kadry, V. Rajinikanth, D. Taniar, R. Damaševičius, and X. P. B. Valencia, “Automated segmentation of leukocyte from hematological images—a study using various CNN schemes,” Journal of Supercomputing, vol. 78, no. 5, pp. 6974–6994, Apr. 2022, doi: 10.1007/s11227-021-04125-4.

[24] R. Mondal, S. Malakar, E. H. Barney Smith, and R. Sarkar, “Handwritten English word recognition using a deep learning-based object detection architecture,” Multimed Tools Appl, vol. 81, no. 1, pp. 975–1000, Jan. 2022, doi: 10.1007/s11042-021-11425-7.

[25] H. Li, Z. Zhou, C. Li, and C. Y. Suen, “A near effective and efficient model in recognition,” Pattern Recognit, vol. 122, Feb. 2022, doi: 10.1016/j.patcog.2021.108173.

[26] L. Jiao, S. Zhang, L. Li, F. Liu, and W. Ma, “A modified convolutional neural network for face sketch synthesis,” Pattern Recognit, vol. 76, pp. 125–136, Apr. 2018, doi: 10.1016/j.patcog.2017.10.025.

[27] Zukisa Nante and Wang Zenghui, “Face Recognition Using Principal Component Analysis, K Means Clustering and,” International Journal of Electrical and Computer Engineering, vol. 16, no. 7, pp. 100–106, 2022.

[28] Y. Cui, Q. Liao, D. Hu, W. An, and L. Liu, “Coarse-to-fine pseudo supervision guided meta-task optimization for few shot object classification,” Pattern Recognit, vol. 122, Feb. 2022, doi: 10.1016/j.patcog.2021.108296.

[29] T. Dai, Y. Feng, B. Chen, J. Lu, and S. T. Xia, “Deep image prior based defense against adversarial examples,” Pattern Recognit, vol. 122, Feb. 2022, doi: 10.1016/j.patcog.2021.108249.

[30] C. Fu, G. Wang, X. Wu, Q. Zhang, and R. He, “Deep momentum uncertainty hashing,” Pattern Recognit, vol. 122, Feb. 2022, doi: 10.1016/j.patcog.2021.108264.

[31] H. Alatrista-Salas, J. Milagros, A. Lopez, E. Leuman, F. Navarro, and M. Nunez-Del-Prado, “Phenotypic Evaluation of Brown Swiss Dairy Cattle Using Images Processing,” 2020.

[32] Y. R. Pandeya, B. Bhattarai, and J. Lee, "Visual object detector for cow sound event detection," IEEE Access, vol. 8, pp. 162625–162633, 2020, doi: 10.1109/ACCESS.2020.3022058.

[33] D. Jarchi, J. Kaler, and S. Sanei, "Lameness Detection in Cows Using Hierarchical Deep Learning and Synchrosqueezed Wavelet Transform," IEEE Sens J, vol. 21, no. 7, pp. 9349–9358, Apr. 2021, doi: 10.1109/JSEN.2021.3054718.

[34] A. Biglari and W. Tang, "A Vision-Based Cattle Recognition System using Tensor-Flow for Livestock Water Intake Monitoring," IEEE Sens Lett, Nov. 2022, doi: 10.1109/LSENS.2022.3215699.

[35] S. Miao et al., "Balanced single-shot object detection using cross-context attention-guided network," Pattern Recognit, vol. 122, Feb. 2022, doi: 10.1016/j.patcog.2021.108258.

[36] Y. Feng et al., "SocialCattle: IoT-Based Mastitis Detection and Control Through Social Cattle Behavior Sensing in Smart Farms," IEEE Internet Things J, vol. 9, no. 12, pp. 10130–10138, Jun. 2022, doi: 10.1109/JIOT.2021.3122341.

[37] S. Ma et al., "Development of Noncontact Body Temperature Monitoring and Prediction System for Livestock Cattle," IEEE Sens J, vol. 21, no. 7, pp. 9367–9376, Apr. 2021, doi: 10.1109/JSEN.2021.3056112.

[38] T. Li, B. Jiang, D. Wu, X. Yin, and H. Song, "Tracking multiple target cows' ruminant mouth areas using optical flow and inter-frame difference methods," IEEE Access, vol. 7, pp. 185520–185531, 2019, doi: 10.1109/ACCESS.2019.2961515.

[39] C. Prabowo et al., "The Implementation of IoT (Internet of Things) for Controlling Cow Health," in IOP Conference Series: Materials Science and Engineering, May 2020, vol. 846, no. 1. doi: 10.1088/1757-899X/846/1/012011.

[40] M. A. Jaddoa, L. Gonzalez, H. Cuthbertson, and A. Al-Jumaily, "Multiview Eye Localisation to Measure Cattle Body Temperature Based on Automated Thermal Image Processing and Computer Vision," Infrared Phys Technol, vol. 119, Dec. 2021, doi: 10.1016/j.infrared.2021.103932.

[41] Y. Uyeno, S. Shigemori, and T. Shimosato, "Effect of probiotics/prebiotics on cattle health and productivity," Microbes Environ, vol. 30, no. 2, pp. 126–132, Jun. 2015, doi: 10.1264/jsme2.ME14176.

[42] A. Giri, V. K. Bharti, S. Kalia, A. Arora, S. S. Balaje, and O. P. Chaurasia, "A review on water quality and dairy cattle health: a special emphasis on high-altitude region," Appl Water Sci, vol. 10, no. 3, Mar. 2020, doi: 10.1007/s13201-020-1160-0.

[43] Y. Qiao et al., "Intelligent perception-based cattle lameness detection and behaviour recognition: A review," Animals, vol. 11, no. 11. MDPI, Nov. 01, 2021. doi: 10.3390/ani11113033.

[44] D. P. Campos et al., "Single-Channel sEMG Dictionary Learning Classification of Ingestive Behavior on Cows," IEEE Sens J, vol. 20, no. 13, pp. 7199–7207, Jul. 2020, doi: 10.1109/JSEN.2020.2977768.

[45] A. Ruchay, K. Dorofeev, V. Kalschikov, V. Kolpakov, K. Dzhulamanov, and H. Guo, "Live weight prediction of cattle using deep image regression," in 2021 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2021 - Proceedings, 2021, pp. 32–36. doi: 10.1109/MetroAgriFor52389.2021.9628547.

[46] C. Li et al., "Data Augmentation for Inertial Sensor Data in CNNs for Cattle Behavior Classification," IEEE Sens Lett, vol. 5, no. 11, Nov. 2021, doi: 10.1109/LSENS.2021.3119056.

[47] W. Zhang, K. Yang, N. Yu, T. Cheng, and J. Liu, "Daily milk yield prediction of dairy cows based on the GA-LSTM algorithm," in International Conference on Signal Processing Proceedings, ICSP, Dec. 2020, vol. 2020-December, pp. 664–668. doi: 10.1109/ICSP48669.2020.9320926.

[48] R. W. Bello, A. S. A. Mohamed, and A. Z. Talib, "Contour Extraction of Individual Cattle from an Image Using Enhanced Mask R-CNN Instance Segmentation Method," IEEE Access, vol. 9, pp. 56984–57000, 2021, doi: 10.1109/ACCESS.2021.3072636.

[49] M. S. Mahmud, A. Zahid, A. K. Das, M. Muzammil, and M. U. Khan, "A systematic literature review on deep learning applications for precision cattle farming," Computers and Electronics in Agriculture, vol. 187. Elsevier B.V., Aug. 01, 2021. doi: 10.1016/j.compag.2021.106313.

[50] Xiaoping Huang, "Cow tail detection method for body condition score using Faster R-CNN," in IEEE International Conference on Unmanned Systems and Artificial Intelligence (ICUSAI)., 2019.

[51] Z. H. Pradana, B. Hidayat, and S. Darana, "Beef cattle weight determine by using digital image processing," in ICCEREC 2016 - International Conference on Control, Electronics, Renewable Energy, and Communications 2016, Conference Proceedings, Jan. 2017, pp. 179–184. doi: 10.1109/ICCEREC.2016.7814955.

[52] K. K. Cevik, "Deep Learning Based Real-Time Body Condition Score Classification System," IEEE Access, vol. 8, pp. 213950–213957, 2020, doi: 10.1109/ACCESS.2020.3040805.

[53] J. D. Ferguson, D. T. Galligan, and N. Thomsen, "Principal Descriptors of Body Condition Score in Holstein Cows," J Dairy Sci, vol. 77, no. 9, pp. 2695–2703, 1994, doi: 10.3168/jds.S0022-0302(94)77212-X.

[54] Y. Qiao et al., "Intelligent perception for cattle monitoring: A review for cattle identification, body condition score evaluation, and weight estimation," Computers and Electronics in Agriculture, vol. 185. Elsevier B.V., Jun. 01, 2021. doi: 10.1016/j.compag.2021.106143.

[55] G. Summerfield, H. Myburgh, A. de Freitas, G. I. Summerfield, and H. C. Myburgh, "A Review of Automated Cow Body Condition Scoring Approaches Using 3D Feature Extraction Improving hearing care access View project Hopfield MLSE equalizer View project A Review of Automated Cow Body Condition Scoring Approaches Using 3d Feature Extraction," 2021, [Online].

Available: https://www.researchgate.net/publication/356716736

[56] T. KOJIMA et al., "Estimation of beef cow body condition score: a machine learning approach using three-dimensional image data and a simple approach with heart girth measurements," Livest Sci, vol. 256, p. 104816, Feb. 2022, doi: 10.1016/J.LIVSCI.2021.104816.

[57] Wen-Yong Li, Yang Shen, Du-Jin Wang, Zhan-Kui Yang, and Xin-Ting Yang, "Automatic dairy cow body condition scoringusing depth images and 3D surface fitting," in International Conference on Unmanned System and Artificial Intelligence (ICUSAI), 2019.

[58] C. Silva, D. Welfer, F. P. Gioda, and C. Dornelles, "Cattle brand recognition using convolutional neural network and support vector machines," IEEE Latin America Transactions, vol. 15, no. 2, pp. 310–316, Feb. 2017, doi: 10.1109/TLA.2017.7854627.

[59] Xinru Li, "Cow Body Condition Score Estimation with Convolutional Neural Networks," in IEEE 4th International Conference on Image, Vision and Computing, 2019.

[60] A. Du, H. Guo, J. Lu, Y. Su, A. Ruchay, and A. Pezzuolo, "Automatic heart girth measurement for cattle based on deep learning," in 2021 IEEE International Workshop on Metrology for Agriculture and Forestry, MetroAgriFor 2021 - Proceedings, 2021, pp. 27–31. doi: 10.1109/MetroAgriFor52389.2021.9628696.

[61] M. H. Na, W. H. Cho, S. K. Kim, and I. S. Na, "Automatic Weight Prediction System for Korean Cattle Using Bayesian Ridge Algorithm on RGB-D Image," Electronics (Switzerland), vol. 11, no. 10, May 2022, doi: 10.3390/electronics11101663.

[62] M. Nahangi, T. Czerniawski, C. T. Haas, and S. Walbridge, "Pipe radius estimation using Kinect range cameras," Autom Constr, vol. 99, pp. 197–205, Mar. 2019, doi: 10.1016/J.AUTCON.2018.12.015.

[63] A. Ghosh and S. Barman, "Application of Euclidean distance measurement and principal component analysis for gene identification," Gene, vol. 583, no. 2, pp. 112–120, Jun. 2016, doi: 10.1016/j.gene.2016.02.015.

[64] B. Ai and Q. Li, "SOLOv2-based multi-view contactless bovine body size measurement," in Journal of Physics: Conference Series, 2022, vol. 2294, no. 1. doi: 10.1088/1742-6596/2294/1/012011.

[65] L. Anifah and Haryanto, "Decision Support System Cattle Weight Prediction using Artificial Selected Weighting Method," in Proceeding - 2020 3rd International Conference on Vocational Education and Electrical Engineering: Strengthening the framework of Society 5.0 through Innovations in Education, Electrical, Engineering and Informatics Engineering, ICVEE 2020, Oct. 2020. doi: 10.1109/ICVEE50212.2020.9243263.

[66] Y. Kawagoe, T. T. Zin, and I. Kobayashi, "Individual Identification of Cow Using Image Processing Techniques," in LifeTech 2022 - 2022 IEEE 4th Global Conference on Life Sciences and Technologies, 2022, pp. 570–571. doi: 10.1109/LifeTech53646.2022.9754899.

[67] B. Xu et al., "CattleFaceNet: A cattle face identification approach based on RetinaFace and ArcFace loss," Comput Electron Agric, vol. 193, Feb. 2022, doi: 10.1016/j.compag.2021.106675.

[68] A. Pretto, G. Savio, F. Gottardo, F. Uccheddu, and G. Concheri, "A novel low-cost visual ear tag based identification system for precision beef cattle livestock farming," Information Processing in Agriculture, Oct. 2022, doi: 10.1016/j.inpa.2022.10.003.

[69] A. Pretto, G. Savio, F. Gottardo, F. Uccheddu, and G. Concheri, "A novel low-cost visual ear tag based identification system for precision beef cattle livestock farming," Information Processing in Agriculture, Oct. 2022, doi: 10.1016/j.inpa.2022.10.003.

[70] M. Ivašić-Kos, M. Krišto, and M. Pobar, "Human detection in thermal imaging using YOLO," in ACM International Conference Proceeding Series, 2019, vol. Part F148262, pp. 20–24. doi: 10.1145/3323933.3324076.

[71] J. Deng, J. Guo, N. Xue, and S. Zafeiriou, "ArcFace: Additive Angular Margin Loss for Deep Face Recognition," 2018, [Online]. Available: https://github.com/

[72] J. Deng, J. Guo, E. Ververas, I. Kotsia, and S. Zafeiriou, "RetinaFace: Single-shot Multi-level Face Localisation in the Wild," 2020.

[73] Zheng Qin, Zhaoning Zhang, Xiaotao Chen, Changjian Wang, and Yuxing Peng, "Fd-Mobilenet: Improved Mobilenet With A Fast Downsampling Strategy," IEEE EXPLORE, 2018.

[74] M. Elkhayati, Y. Elkettani, and M. Mourchid, "Segmentation of Handwritten Arabic Graphemes Using a Directed Convolutional Neural Network and Mathematical Morphology Operations," Pattern Recognit, vol. 122, Feb. 2022, doi: 10.1016/j.patcog.2021.108288.

[75] G. Summerfield, H. Myburgh, A. de Freitas, G. I. Summerfield, and H. C. Myburgh, "A Review of Automated Cow Body Condition Scoring Approaches Using 3D Feature Extraction Improving hearing care access View project Hopfield MLSE equalizer View project A Review of Automated Cow Body Condition Scoring Approaches Using 3d Feature Extraction." [Online]. Available: https://www.researchgate.net/publication/356716736

[76] R. Garcia, J. Aguilar, M. Toro, and M. Jimenez, "Weight-Identification Model of Cattle Using Machine-Learning Techniques for Anomaly Detection," in 2021 IEEE Symposium Series on Computational Intelligence, SSCI 2021 - Proceedings, 2021. doi: 10.1109/SSCI50451.2021.9659840.

[77] F. Tian, J. Wang, B. Xiong, L. Jiang, Z. Song, and F. Li, "Real-Time Behavioral Recognition in Dairy Cows Based on Geomagnetism and Acceleration Information," IEEE Access, vol. 9, pp. 109497–109509, 2021, doi: 10.1109/ACCESS.2021.3099212.

[78] F. Bousefsaf, A. Pruski, and C. Maaoui, "3D convolutional neural networks for remote pulse rate measurement and mapping from facial video," Applied Sciences (Switzerland), vol. 9, no. 20, Oct. 2019, doi: 10.3390/app9204364.

[79] S. Hizlisoy, S. Yildirim, and Z. Tufekci, "Music emotion recognition using convolutional long short term memory deep neural networks," Engineering Science and Technology, an International Journal, vol. 24, no. 3, pp. 760–767, Jun. 2021, doi: 10.1016/j.jestch.2020.10.009.

[80] Y. Qiao, Y. Guo, K. Yu, and D. He, "C3D-ConvLSTM based cow behaviour classification using video data for precision livestock farming," Comput Electron Agric, vol. 193, Feb. 2022, doi: 10.1016/j.compag.2021.106650.

.

NOMENCLATURE

σ= smooth scale
PB = Cow Body Length
LD = Cow Body Circumference

AUTHOR(S) BIOGRAPHY

Zurnawita
Doctoral student of Electrical Engineering, Andalas University and also a lecturer in the Bachelor of Applied Telecommunication Engineering study program in the field of image processing who has a career of more than 20 years

 https://doi.org/10.25077/jitce.7.01.8-18.2023