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Development of an Artificial Intelligence Deep Neural Network for the Identification of Individual Animals

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Abstract

Monitoring of individual animals and their feeding habits can pose a challenge to farmers to prevent under- or overfeeding of individual animals. A system that can identify individual animals and allows feeding or medicating of a specific animal will increase productivity, profitability and animal condition. The objective of the research is the development of an automated system, making use of video and image processing techniques, as well as deep learning neural networks, to identify individual animals. Using Matlab®, Python and Google Colab the principles of neural networks (NN) and Artificial Intelligence (AI) learning was tested and evaluated on a personal computer and will later be implemented on suitable portable hardware. Results will be verified and the suitability for such a project will be tested and judged by evaluating the accuracy of the recognized images. Initial tests indicated that an Artificial Neural Network (ANN) proved to be sufficient and could be run on compact hardware such as the NVIDIA Jetson Nano. A small amount of learning material could be used and proofed to be successful in identifying cattle heads on such a device.

Keywords: deep learning neural networks, animal feeding, animal identification, video and image processing techniques, Artificial Intelligence, NVIDIA, Jetson Nano

3. Introduction

Feeding animals a balanced diet is crucial for modern farming, as over- or underfeeding can lead to financial losses and impact the farm's profitability [1]. The concept of balanced nutrition for animals was identified during the late 19th century when industrial-scale production of animal feeds began [2]. While natural grazing can meet the nutritional needs of farm animals, supplementing with concentrated nutrients might be necessary [3]. The quality of the feed is influenced not only by nutrient content but also factors like presentation, hygiene, digestibility, and intestinal health [3] [4] [5].

To ensure proper feeding, it's important to consider the different digestive systems of various livestock species. Farmers can supplement normal feed with industry by-products like distiller's grains and soybeans, which is environmentally sustainable and economically beneficial [6]. Automatic feeding systems are also becoming popular on farms in some European countries to ease workload and improve flexibility [7].

In South Africa, animal production plays a significant role in the economy [8], especially since much of the agricultural land can only be utilized for livestock. Livestock production contributes to food security and has social and economic impacts in the country [9].
The study in question aims to explore the use of a portable AI development kit, the NVIDIA Jetson Nano, to implement a machine vision system in farming. The system's objective is to autonomously identify individual animals in a farming environment using AI and machine vision algorithms.

2. Methods of identification

Different methods of marking animals for identification exist, categorized as permanent and non-permanent. Non-permanent methods include cutting the tail brush and using color markers like paint. Permanent methods involve ear notching, ear tags, tattoos, hot iron branding, freeze branding, and electronic markers [10].
Certain cattle breeds like Nguni and Friesland have unique color markings comparable to thumbprints [10], allowing individual identification through image processing techniques. Photos can be taken and stored for this purpose. Image sensors are increasingly used in biodiversity monitoring, generating vast amounts of pictures [11]. Efficiently identifying species in each image is a critical challenge in this field.
AI, according to Matcher [12], can be successfully employed to identify specimens, making science more accessible. By using AI, the success rate and reliability of image recognition can be improved.

2.1. Current methods of identification of animals

In the study by Taha et al. on the identification of Arabian horses, current methods for animal identification were explored. These methods include freeze-branding, hot-iron branding, hooves marker, lip tattooing, ear tags, and neckbands. However, the study highlights that these traditional methods can lead to painful infections, duplication, and fraud issues [13].

2.2. New methods of identification of animals

New methods of animal identification have emerged through advancements in technology. These methods include microchips inserted into the neck, Radio Frequency Identification (RFID) tags, radio tracking, wireless sensor network tracking, satellite and GPS tracking, and motion-sensitive camera traps. However, some drawbacks exist with microchips and RFID tags, such as the potential for loss or malfunction, misreading, and possible damage to animal body parts [13] [14].
Camera traps offer an affordable way to collect high-resolution images and data on wildlife, but manual data collection and analysis are required. Challenges arise due to partial images, long distances, and poor lighting conditions [15].
To address these issues, a biometric solution has been proposed, relying on animal features like iris, retina, DNA, or patterns unique to specific breeds (e.g., Nguni cattle). Salama et al. successfully used convolutional neural networks (CNNs) to identify Arabian horses based on their iris patterns with an accuracy of 97.6%. However, this method may not be universally applicable to all animal types due to variations in eye structures [16].

3. Artificial Intelligence and Machine Learning

The term AI lacks a precise definition, but it involves artificial activities that can be interpreted as intelligence, including learning, reasoning, and understanding. Computers can simulate intelligence through various steps, such as setting goals, gathering and manipulating data, defining relationships, and assessing goal achievement [17].

Machine learning (ML) is a form of automated learning where computers learn from available inputs to gain expertise or knowledge. AI encompasses machine learning, and within machine learning, there is a subset called deep learning [18].

Figure 1 illustrates the process of machine learning, where a model or algorithm is developed from data [19].

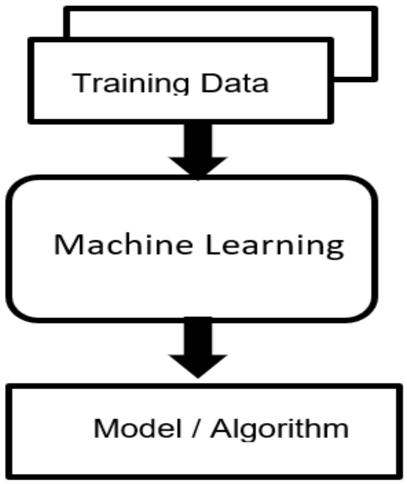

Figure 1 Process when machine learning occurs.

Figure 1 shows the training process, where a deep-learning framework and a training dataset of cattle photos were used to create a machine learning algorithm. The images were labeled using the labelImg tool, and the training was conducted on Google Colab with 209 images.
After the algorithm is trained, it can be applied to real-world data for implementation [19], as shown in Figure *2*.

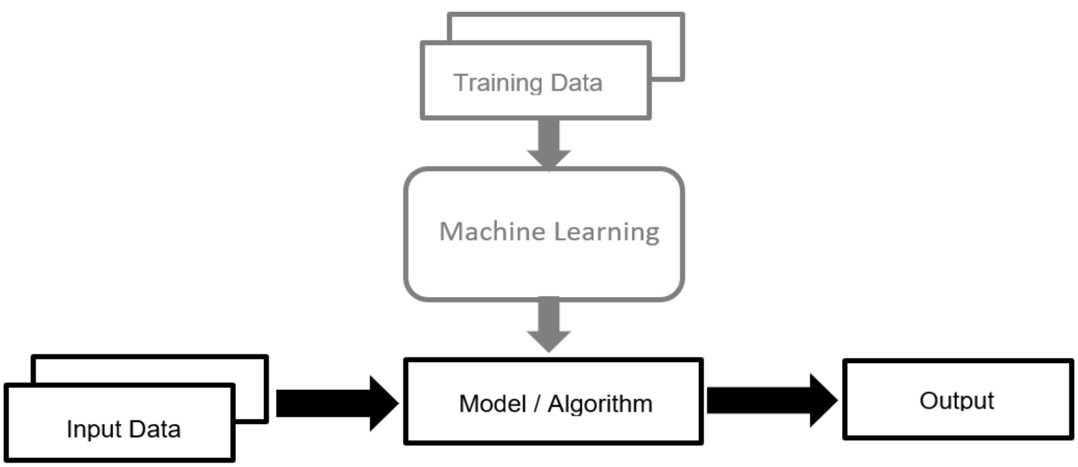

Figure 2 Implementation of Trained Algorithm

The hardware platform's size and performance have a direct relationship with the AI platform's decision-making capabilities [17]. Inference time refers to the processing duration of using a trained machine learning algorithm to make predictions or obtain outputs from real-world data, like images [20]. Imran Bangash conducted a benchmark of three widely used AI hardware accelerators: Intel Movidius NCS stick, Google Coral USB stick, and NVIDIA Jetson Nano, as shown in the comparison study [21].

Table 1 Popular AI hardware specifications

Parameters	Nvidia Jetson Nano	Google Coral USB	Intel Movidius NCS
Inference time	~38 ms	~70 – 92.32 ms	~225-227 ms
Fps	~25	~9-7	~4.43 – 4.39
CPU usage	47-50%	135%	87-90%
Memory usage	32%	8.7%	7%

Based on the results, the NVIDIA Jetson Nano stands out as a suitable choice for implementing an AI system due to its low inference time [22]. Comparing its specifications with other available systems, the NVIDIA Jetson Nano performs exceptionally well with various neural networks and AI tasks. However, NVIDIA also released the NVIDIA Xavier NX in May 2020, targeting the professional and commercial market with even higher performance capabilities. Despite its increased performance, the NVIDIA Xavier NX comes at a significantly higher price of 399 USD, while the NVIDIA Jetson Nano is priced at 99 USD [23].

4. Artificial Neural Networks

To improve the quality of farming products, frequent visits to production areas are necessary, but they can increase farming costs [24]. Internet of Things (IoT) technologies enable monitoring of animals and crops, providing data on factors like rainfall, soil moisture, plant height, and water availability for animals. However, to truly make farming smart and affordable, additional processes like observation, diagnosis, decision making, and action are essential [24]. Automating data analysis of collected camera images can be achieved using Artificial Neural Networks (ANNs). Nasser et al. achieved 100% accuracy in predicting animal categories with ANNs, but individual identification within the same category or species was not addressed [18].

ANNs are ML models inspired by the structure and function of the human brain, comprising interconnected nodes (artificial neurons) that learn from data and process information. They find applications in classification, regression, pattern recognition, and prediction tasks and have been successfully employed in various fields like computer vision, natural language processing, and robotics. The ability of ANNs to learn from large and complex datasets makes them powerful tools for solving real-world problems.

5. Capturing, analysing of pictures and creating a database of animals

Rivas et al. [25] utilized drones to capture aerial images of cattle in fields and employed Convolutional Neural Networks (CNNs) to identify cattle in the images. While the CNNs successfully identified cattle, individual animals were not distinguished [25].

To achieve identification of different types and individual animals, the next step involves building a database of images of individual animals. This process will entail creating a library of known animals and designing a deep neural network for animal recognition. Research efforts will focus on capturing high-quality or low-quality photo and video images that can be used for animal "face" identification.

The project aims to strike a balance between the amount of data collected and the successful identification of animals, utilizing different sources of collected data.

Figure 3 provides a graphical overview of the project's approach [25].

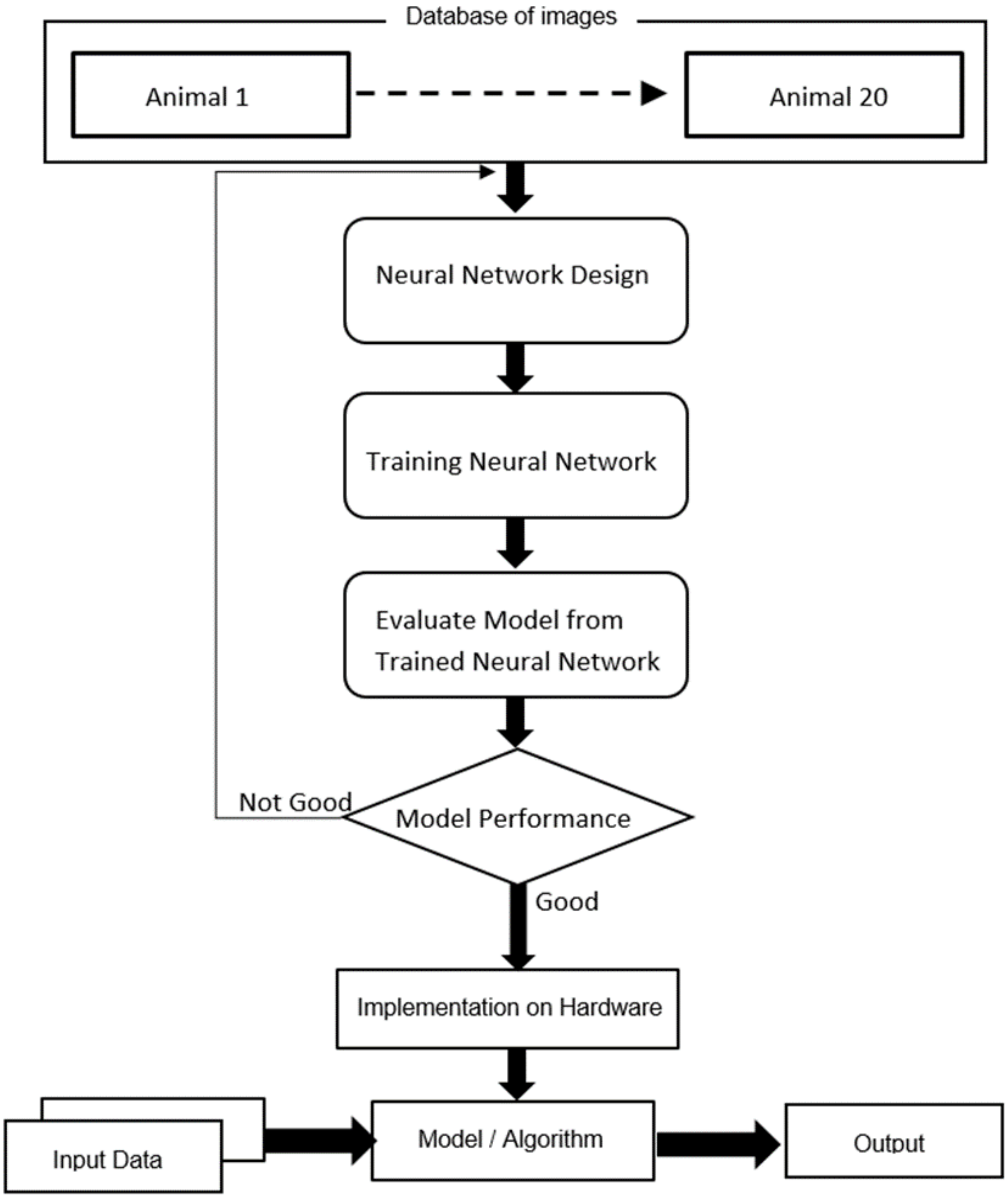

Figure 3 Overview of Project.

6. Initial Tests

Initially a Speeded-Up Robust Features (SURF) method was tested. This was chosen due to the fast computation ability of SURF for real-time applications [26]. Using SURF methods, experiments were done in MATLAB®, to establish the suitability of this method to identify individual animals.

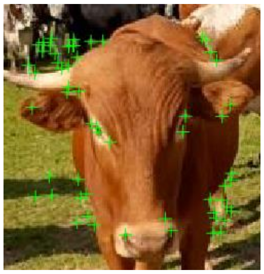

Figure 4 Plot Valid Corner Points

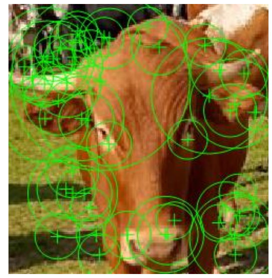

Figure 5 Extracted and display of the SURF Features

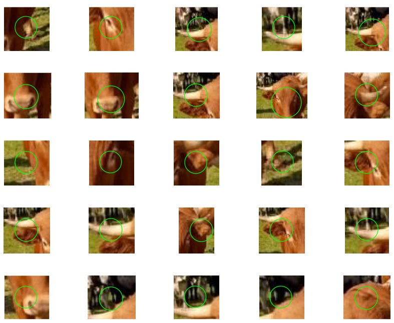

Figure 6 Interest Areas

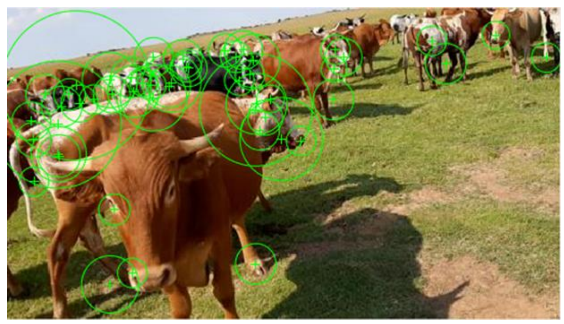

Figure 7 Combined Interest Areas

Figure 6 depicts 25 interest areas identified in the image while Figure 7 shows the combined interest areas in the original source image.

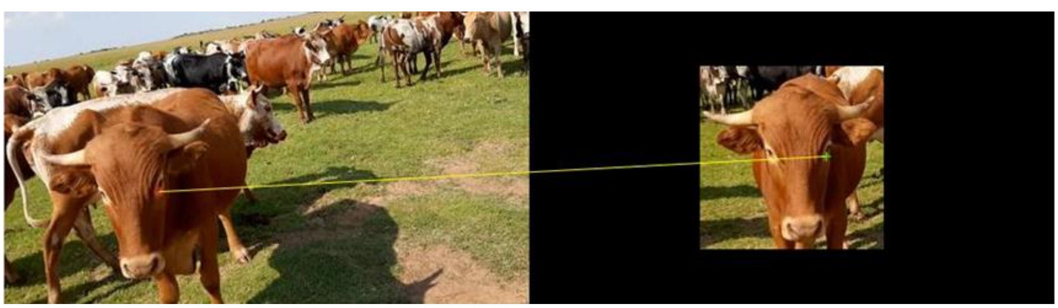

Figure 8 Feature Matching

The SURF algorithm could identify points of interest in images, but Figure 8 demonstrated that it wasn't suitable for individual cattle identification as it only matched one feature, despite the images being nearly identical. To address this, the decision was made to explore the You Only Look Once (YOLO) deep learning model for image recognition. YOLO is popular for real-time object detection in images or videos, known for its speed and efficiency, making it ideal for applications like autonomous driving, surveillance, and robotics.

YOLO provides bounding boxes, class labels, and confidence scores as its output, which offer information about detected objects and their locations in the image. YOLO's key advantage is its single-pass detection approach on the entire image, allowing real-time performance without sacrificing accuracy.

A YOLOv3 system was trained with cattle head images and implemented on MATLAB®. Figure 9 showcases the successful results of YOLOv3 identifying cattle heads from a photo, with training conducted using Google Colab Notebooks.

Figure 9 Implementation of YOLOv3 to identify cattle heads.

Figure 10 shows a captured frame from a more ‘crowded’ video source to identify cattle heads with YOLOv3 on MATLAB®.

Figure 10 Implementation of YOLOv3 to identify cattle heads.

In this instance, the systems successfully detected 35 cattle heads with a confidence threshold of 0.9 and above. Figure 11 and Figure 12 display the 15 cattle heads with the highest threshold scores, marked with yellow rectangles. The inference time for each video frame varied between 82.6981 and 87.5616 seconds.

The tests were conducted on a computer with an Intel® Core™ i5-6500 CPU @ 3.20GHz, 32GB RAM, and a Windows 10 Pro 64-bit operating system. While the computer possessed an NVIDIA GeForce GTX1070 graphics adaptor, it was not utilized in the initial tests.

Furthermore, comparable results for cattle head identification were obtained when implementing a YOLO system on a Jetson Nano.

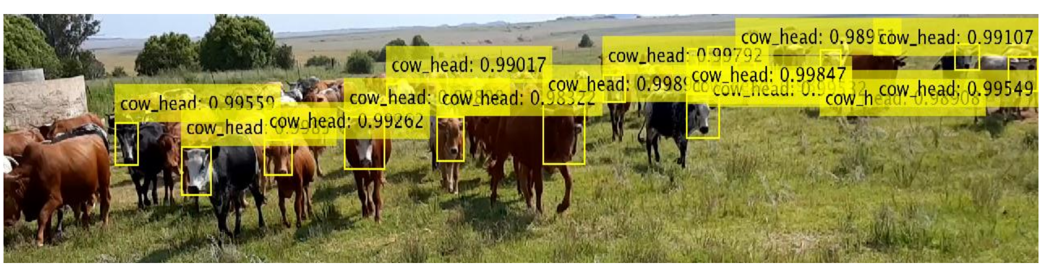

Figure 11 Implementation of YOLOv3 to identify cattle heads.

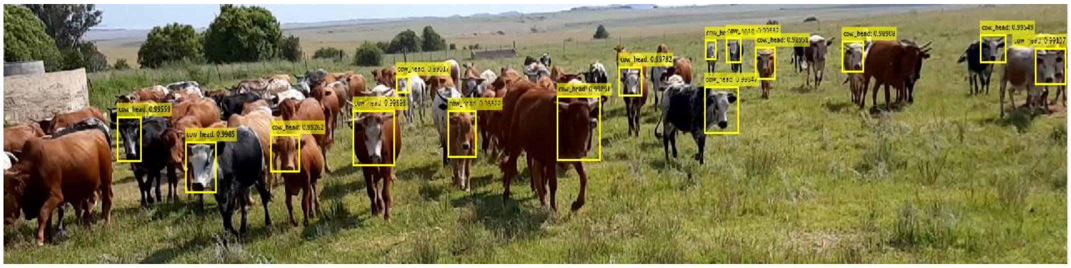

Figure 12 Identification of cattle heads.

Figure 12 depicts the 15 identified cattle heads but the boxes are reformatted, to see the identified cattle heads better.

7. Conclusion

The algorithms developed on the PC demonstrated successful identification of cattle heads and, to a lesser extent, individual animals. The effectiveness of AI-based identification heavily depends on the quality and diversity of the training data. Improvements are needed in the algorithms and training process to achieve better identification of individual animals. However, the successful identification of cattle heads will aid in automating the generation of training data, which will ultimately enhance the training of algorithms.

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