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A machine vision system to predict individual cow feed intake of different feeds in a cowshed

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ABSTRACT

Data on individual feed intake of dairy cows, an important variable for farm management, are currently unavailable in commercial dairies. A real-time machine vision system including models that are able to adapt to multiple types of feed was developed to predict individual feed intake of dairy cows. Using a Red-Green-Blue-Depth (**RGBD**) camera, images of feed piles of two different feed types (lactating cows' feed and heifers' feed) were acquired in a research dairy farm, for a range of feed weights under varied configurations and illuminations. Several models were developed to predict individual feed intake: two Transfer Learning (**TL**) models based on Convolutional Neural Networks (**CNNs**), one CNN model trained on both feed types, and one Multilayer Perceptron and Convolutional Neural Network model trained on both feed types, along with categorical data. We also implemented a statistical method to compare these four models using a Linear Mixed Model and a Generalised Linear Mixed Model, showing that all models are significantly different. The TL models performed best and were trained on both feeds with TL methods. These models achieved Mean Absolute Errors (**MAEs**) of 0.12 and 0.13 kg per meal with RMSE of 0.18 and 0.17 kg per meal for the two different feeds, when tested on varied data collected manually in a cowshed. Testing the model with actual cows' meals data automatically collected by the system in the cowshed resulted in a MAE of 0.14 kg per meal and RMSE of 0.19 kg per meal. These results suggest the potential of measuring individual feed intake of dairy cows in a cowshed using RGBD cameras and Deep Learning models that can be applied and tuned to different types of feed.

Implications

Data on individual feed intake of dairy cows, an important variable for farm management, are currently unavailable in commercial dairies. We developed a system utilising a Red-Green-Blue-Depth camera for measuring an individual cow's feed intake in a cowshed, and a Convolutional Neural Network with transfer learning methods, enabling adaptation to different feeds. In an experiment conducted in a research cowshed, the system error was found to be sufficiently low. This system can be utilised to identify individual eating behaviour, and efficient and inefficient cows. Adapting to different feeds is an important feature for dairy farms.

Introduction

Individual cow feed intake is a significant factor for dairy management; more than 60% of farm expenses are devoted to feed (Bloch et al., 2019; Buza et al., 2014; Halachmi et al., 2016). This major economic impact of feed intake in dairy production has motivated genetic studies on moderately heritable traits of feed intake and nutrient utilisation efficiency (Korver, 1988; Vandehaar, 1998; Berry et al., 2014). Despite this, genetic selection based on individual feed efficiency has not been widely applied, mainly due to the high cost and practical limitations of individual feed intake measurements (Berry et al., 2014; Seymour et al., 2019). Feed conversion effectiveness can be determined using information about a cow's feed intake, and milk production and composition (National Research Council, 2001; 2007; Volden, 2011). Hence, monitoring feed intake can improve farm management decisions (Shalloo et al., 2004), which is potentially beneficial for farm productivity (Buza et al., 2014; Halachmi et al., 2016; Herd et al., 2003).

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Different feed intake measurement systems have been developed, including electronic scales in the feeding stalls to measure the feed consumed by each cow. These weighing systems have been used by several researchers (Bach et al., 2004; Halachmi et al., 1998; Chapinal et al., 2007). Both self-designed weighing systems and commercial systems are available primarily for research institutions, rather than for commercial cowsheds, due to their high cost, additional infrastructure, high maintenance, and frequent cleaning requirements, all of which make them impractical for most commercial farms (Stajnko et al., 2010; Wang et al., 2006).

In order to evaluate the mass of the feed, an image processing algorithm can be utilised. Feed mass evaluations based on cameras were performed by using structured light illumination methods (Shelley, 2013), by implementing light detection and ranging sensing methods (Shelley et al., 2016), and by using 3D Time-of-Flight camera when protected from the sun (due to infrared light contained in sunlight) (Borchersen et al., 2018; Lassen et al., 2018). Those methods are impractical on a commercial farm mainly due to their sensitivity to sunlight. Bloch et al. (2019) attempted to overcome the sunlight issue using a photogrammetry method resulting in estimated errors of 0.483 kg for heaps up to 7 kg under laboratory conditions, and 1.32 kg for heaps up to 40 kg in a cowshed. However, this method requires multiple high-quality Red-Green-Blue (**RGB**) cameras per feed pile measurement along with coloured markers; hence, it is impractical for a cowshed on a commercial farm.

Machine vision (**MV**) and deep learning methods have made technological advances in recent years (Szegedy et al., 2016). Deep learning and specifically convolutional neural networks (**CNNs**) are a discipline in the machine learning field and can be used for complicated MV tasks such as classification, detection, and recognition (Bezen et al., 2020). CNNs are based on non-linear, end-to-end training which requires the learning of many parameters. Thus, they require large amount of diverse data (Ros et al., 2016). Few studies have been conducted in the field of feed intake measurements using neural networks (Bezen et al., 2020; Chen et al., 2020; Shen et al., 2021). In a recent study (Bezen et al., 2020), an MV system using a Red-Green-Blue-Depth (**RGBD**) camera was designed, and a CNN was compared with and without RGB function. The MAE and RMSE obtained per meal were 0.127 and 0.184 kg, respectively. However, the performance of the model was measured using images of heaps spread manually and not images of actual cows' meals. The aim of this study was to develop a new MV system for monitoring individual feed intake in an outdoor cowshed. Several new learning models were developed, trained, and compared; the best model was validated on actual cows' meals in a real environment.

Material and methods

Data collection

There were two phases of data collection: manual collection for training, testing and statistically comparing several deep learning models, and automatic collection for validation of the best deep learning model obtained. Both manual and automatic data collections were conducted at a research cowshed at the Volcani Agricultural Research Organisation (Israel). A group of 60 Holstein cows participated in the automatic data collection process.

Two feeds were used in the manual collection phase, and a single feed type (eaten by lactating cows) was used in the automatic collection phase:

Feed eaten by lactating cows (feed type A) included the following components: wheat silage (37.7%), ground corn grain (18.1%), wheat hay (9.4%), lactose waste (7.8%), gluten feed (7.5%), corn distilled dry grain (4.7%), rapeseed meal (3.7%), wheat grain (2.5%), soybean meal (2.5%), barley grain (0.8%) and vitamins and microelements.

Feed eaten by heifers (feed type B) included the following components: straw (33.2%), gluten feed (12.2%), ground corn grain (11.5%), wheat hay (11.1%), wheat grain (8.8%), cotton seed (8.8%), sunflower meal (7%), vitamins and trace minerals (3.9%) and lactose waste (3.5%).

Manual data collection for training, testing, and comparing models

In order to obtain a varied dataset for training, data of two feed types were collected in September 2020, over a period of 10 days in 10 different sessions (5 sessions for each feed type). The weights of the piles were in the range of 0–45 kg for feed type A, and 0–22 kg for feed type B. To ensure a diverse dataset, images of each pile of the same weight were acquired multiple times, in multiple pile arrangements, illuminations, and at different time periods during the day (as described in Table 1).

The acquisition process was as follows: an off-the-shelf Intel RealSense depth camera (D435, Intel, USA) was installed on an aluminium rod 130 cm above the feed lane. The camera was connected to a computer (equipped with an Intel Core i7-7500U processor). A Python script (van Rossum, 1995) was developed to operate the camera. An electronic scale was used to weigh the feed piles using a 1 000 kg loadcell with 0.023% precision (SQB, Keli CEE, Poland). Each pile was manually weighed and then manually spread on the ground before acquiring an image.

Automatic data collection for validation

An automatic system for measuring feed intake was designed, built, and installed for about 4 weeks in March 2021 in the research cowshed. First, in order to fine-tune the trained model with data collected under different conditions (different surface and diverse illumination conditions caused by the different seasons and times along the day), 300 images of feed piles of feed type A were manually acquired and labelled. Thereafter, the system operated automatically collecting data of feed type A.

The system included two feeding stations (Fig. 1). Each station was equipped with a camera, and both cameras were connected to the same computer. In addition, a 17w LED bulb was positioned next to each camera and illuminated each feed pile during dark hours. Thus, the feed piles were lit uniformly, and shadows were minimised. A station including a weighing palette alongside the camera was used as a calibration station. The weighing palette was attached to an electronic scale built of four loadcells. The signal from the load cells was amplified by a load cell amplifier (HX711, SparkFun Electronics, USA) and read by an Arduino micro-

Table 1
Manual data collected at a research cowshed for both feeds.

Session	Feed type	Condition	Number of images
1	A	Daylight – morning hours	185
2		Daylight – afternoon hours	185
3		Daylight – afternoon hours	170
4		Dark using 17w led bulb – night hours	159
5		Direct sun – morning hours	66
6	B	Daylight – morning hours	180
7		Daylight – afternoon hours	170
8		Daylight – morning hours	186
9		Dark using 17w led bulb – night hours	170
10		Direct sun – morning hours	66
			1 537

Abbreviations: A = lactating cows' feed; B = heifers' feed.

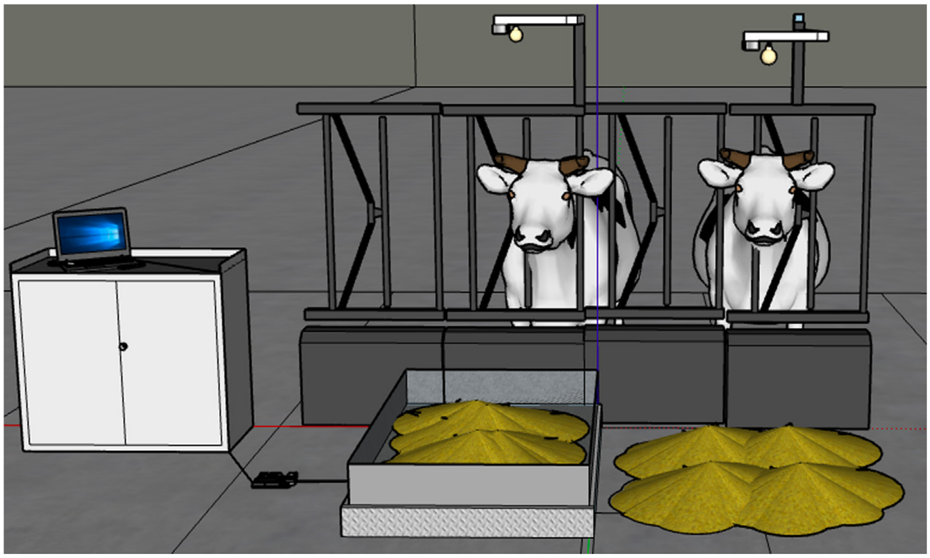

Fig. 1. Illustration of the automatic system installed in the cowshed consisting of two feeding stations, cameras, computer, weighing palette, LED lights.

controller (Mega, Arduino, Italy), which streamed the weight readings to the computer. The weighing palette measured 1 × 1.5 metres, corresponding to the size of a single feeding area at the dairy farm in which the study was conducted. In both stations, when a cow entered the feeding station, motion was detected with a motion detection algorithm that uses Gaussian blurring and binary thresholding (Bezen et al., 2020). Data from the RGBD camera and the weight of the feed pile were acquired before and after a cow ate from the feed piles. A total of 2 000 entrances to the calibration station were detected, resulting in 2 000 actual meals eaten by cows.

Datasets for training and fine-tuning

The datasets included tensors (i.e., multidimensional arrays) representing single meals. Each tensor was assembled by subtracting a lower pile weight image from a higher one (for RGB and depth channels, i.e., four channels for each tensor). Moreover, for each tensor, two categorical variables representing the type of feed and the period of time during the day in which the image was taken (morning/afternoon/night) were created.

The tensor creation process included the following steps: (a) Assembling meals in the range of 0–6 kg fresh weight per meal (i.e., 'as fed', not DM). (b). Data augmentation: before subtraction of two images, horizontally and vertically flipping augmentations were performed on the original image, such that from each subtraction of two images, two different meals emerged. Augmentation was randomly performed on some of the images (about 30%) to increase the dataset while avoiding creation of a too homogenous dataset. (c) Concatenating the subtracted RGB and depth images to create 4-channel tensors. (d) Resizing the tensors (160, 120, 4). (e) Coding the categorical variables as follows: the type of feed variable was binary coded (1 for feed A and 0 for feed B) and the time period variable was one-hot encoded. The one-hot encoding technique is one of the most common ways to transform categorical features into numerical data which is a suitable format used as input for neural networks (Seger, 2018).

Approximately 30 000 RGBD tensors were created from the manually collected data for each feed type. From these tensors, three datasets were created for the training phase: (1) Tensors of feed type A, (2) Tensors of feed type B, (3) Tensors of both feed types (50% tensors from each type). All datasets were distributed approximately uniformly between the different weights in the range of 0–6 kg. An additional 7 000 RGBD tensors were created for model fine-tuning, using the 300 images manually collected in March 2021.

Developing learning models to adapt to different feed types

The following models were developed, trained, tested, and compared:

(1) Combined model: trained using tensors of both feed types.

The model was trained using a dataset of 40 000 tensors where 50% of the data were from each of the feed types. This was done without indicating to the model which feed type was captured in each tensor.

(2) Transfer Learning (**TL**): (a) A CNN model was trained using 30 000 tensors of feed type A, and fine-tuned to adjust this model to predict weights of feed type B, using a dataset of 22 670 tensors of feed type B. (b) A CNN model was trained using 30 000 tensors of feed type B, and fine-tuned to adjust this model to predict weights of feed type A, using a dataset of 24 000 tensors of feed type A.

(3) Multilayer Perceptron and Convolutional Neural Network (**MLP-CNN**) model using multiple inputs of mixed data: this model was trained using the same dataset as model (1), with two additional categorical variables in the model's input, representing the type of feed in each tensor and the time period at which the image was taken.

Models (1) and (2a, 2b) used an architecture which was developed during this study (Fig. 2a, Table 2) and inspired by the EfficientNet B0 baseline model (Tan and Le, 2019). The architecture was composed of six inverted residual blocks. Each block included a batch normalisation layer, a convolutional layer, and a depthwise convolutional layer. To avoid overfitting on the training set, an early stopping method was used to stop the training process when the model's performance stopped improving. Finally, the loss function was mean squared error, and the optimiser was root mean square propagation.

Model (3) used an MLP-CNN architecture for mixed data (categorical and images data) which was developed during this study (Fig. 2b). The MLP network was used to handle the categorical data (i.e., type of feed and time period) and the CNN was used to extract features from the tensors. The MLP network was composed of multiple Fully Connected (**FC**) layers. The CNN was similar to the one

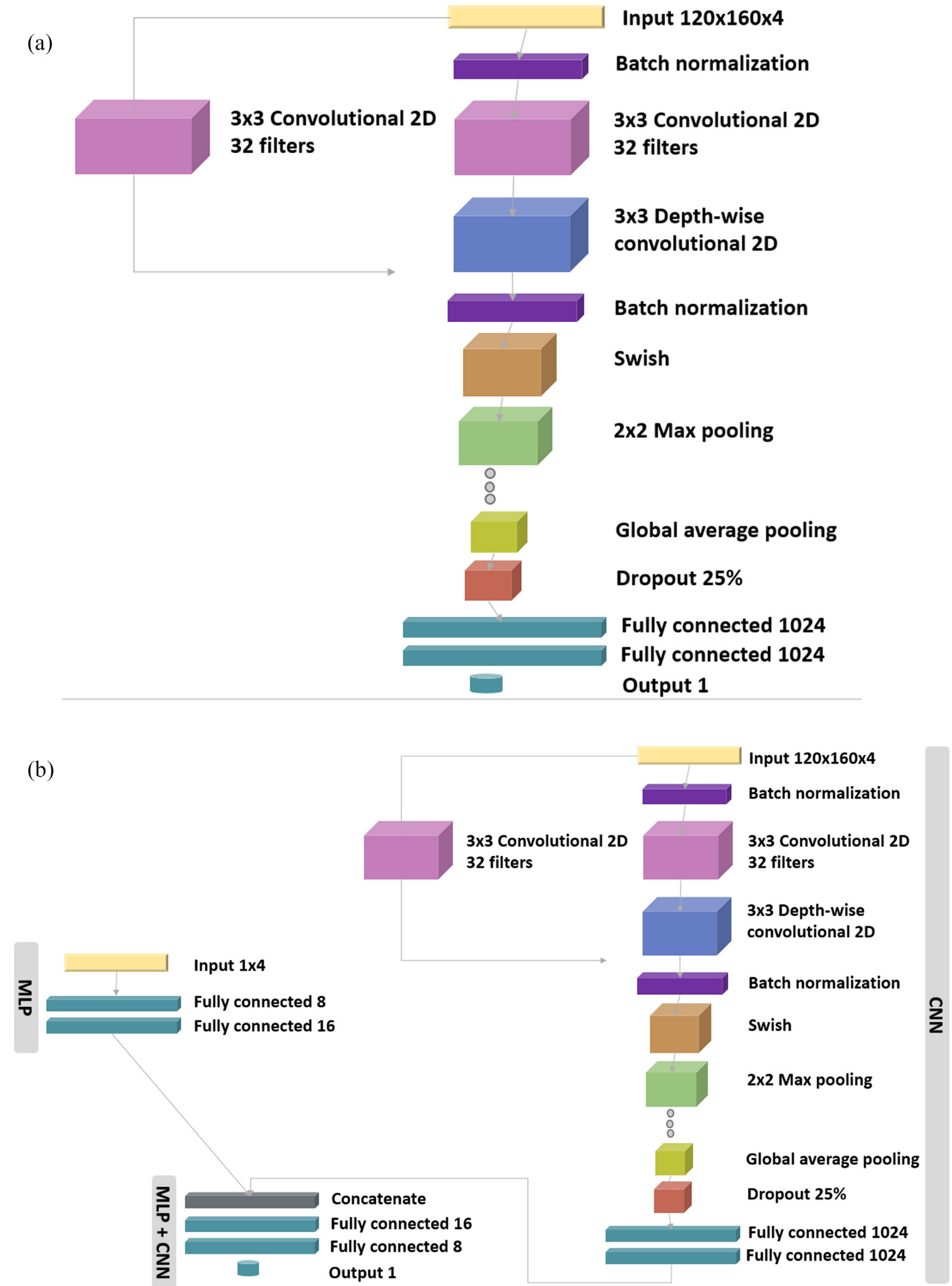

Fig. 2. Development of Convolutional Neural Network (CNN) (a): the network developed was inspired by EfficientNet B0 baseline model. Development of Multilayer Perceptron and Convolutional Neural Network (MLP-CNN) (b): combining CNN and MLP together where the MLP addition allows us to insert categorical data to the network.

used in models (1) and (2) besides the final output layer which was removed. Finally, the outputs of both networks were concatenated and inserted as the input of multiple FC layers, in order to make the final prediction of the weight of each meal.

The outputs of the models were continuous values (feed intake per meal in kg). The dataset of each model was split into training and test sets. Twenty percent of the data were randomly selected and used to test the model, and the remaining 80% of the data were

Table 2
Convolutional Neural Network (CNN) models' hyperparameter values.

Hyperparameter	Value
Learning Rate (maximum)	0.001
Learning Rate (minimum)	$6.25 \cdot 10^{-5}$
Batch size	16
Dropout rate	0.25
Regulariser	0.01

Table 4
Linear mixed model (LMM) and generalised linear mixed model (GLMM) analysis.

Model[1]	Estimated marginal means	
	LMM	GLMM
Model 1	0.02	0.04
Model 2a	−0.004	0.02
Model 2b	−0.02	0.02
Model 3	0.006	0.04

[1] See Table 3 for model descriptions.

used for training. All the models were trained on NVIDIA GeForce GTX 1080ti GPU, Intel Core™ i7-8700, 64-bit six-core 3.2 GHz CPU, 32 GB memory running on Microsoft Windows 10 system.

Analysis

The sensitivity of the models to the training and test sets, obtained from the manually collected data, was evaluated using 5-fold cross-validation. The tensors of each fold were randomly selected after the tensors' creation process. The overall performance of each model (mean absolute error (**MAE**) and RMSE) was computed by averaging the outcomes of all the five folds. To examine if one of the models had significantly better performance compared to the rest, a linear mixed model (**LMM**) and a generalised linear mixed model (**GLMM**) were used (Laird and Ware, 1982): $y - \hat{y} = model + (1|sample\ \ id)$ and $(y - \hat{y})^2 = model + (1|sample\ \ id)$, respectively. The LMM examined each model's bias, and the GLMM determined which model resulted in the lowest squared residual. Moreover, *posthoc* pairwise comparisons were conducted using Tukey method to determine whether the models were significantly different. All analyses were performed using the R statistical package at the 0.05 significance level.

Results

Manual data collection

The minimum average error rate using 5-fold cross-validation was 0.12 kg MAE and 0.18 kg RMSE per meal for feed type A, and 0.13 kg MAE and 0.17 kg RMSE per meal for feed type B, for an average meal weight of 2.92 kg (model 2a, Table 3). *Posthoc* analysis revealed significant differences between the learning models ($P < 0.0001^{***}$). Model 2a resulted in the lowest bias when predicting the error, and it underestimated the weights of the predicted meals based on the LMM analysis (Table 4). Both models 2a and 2b resulted in the smallest residual in predicting the squared error based on the GLMM analysis (Table 4).

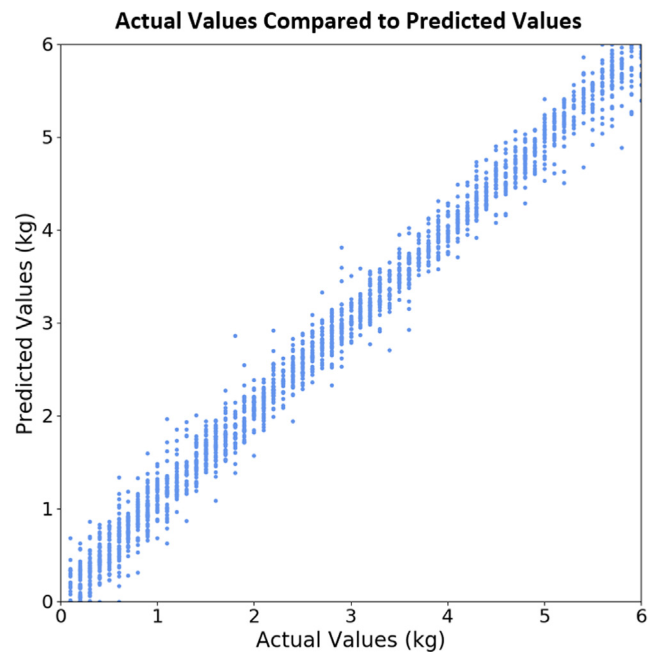

Fig. 3. Lactating cows' feed intake predicted values vs. actual values. X and Y axes are the weight in kg.

Automatic data collection

Using model 2a with the automatically collected data resulted in an MAE of 0.14 kg per meal, and an RMSE of 0.19 kg per meal for an average meal weight of 2.75 kg. Correlation between the actual values and the model predictions is presented in Fig. 3.

Table 3
Average performance (kg per meal) of the models utilising five different datasets created from the manually collected data at the research cowshed.

Learning Model	MAE	RMSE	SD
Model 1 – Combined	0.18	0.26	0.26
Model 2a – TL			
Feed type A	0.12	0.18	0.18
Fine-tune to feed type B	0.13	0.17	0.17
Model 2b – TL			
Feed type B	0.1	0.14	0.13
Fine-tune to feed type A	0.16	0.22	0.21
Model 3 – MLP-CNN	0.17	0.25	0.25

$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$; $RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$
Abbreviations: MAE = mean absolute error; TL = transfer learning; MLP-CNN = Multilayer Perceptron and Convolutional Neural Network; A = lactating cows' feed intake; B = heifers' feed intake.
Model 1 – tensors of both feeds; Models 2a, 2b – TL from one feed to the other; Model 3 – tensors of both feeds in addition to two categorical variables.

Discussion

The minimum error (MAE of 0.14 and RMSE of 0.19 kg per meal) reported in this study, when tested on data collected automatically by the MV system in an outdoor cowshed, was lower than that achieved in earlier studies (Shelley et al., 2016; Bloch et al., 2019). The minimum error was close to the error reported in a previous study (Bezen et al., 2020). However, the system of Bezen et al. (2020) was tested on feed piles that were created manually without using actual piles created by cows. In the current study, the images for validation were automatically acquired from actual cows' meals in a dairy farm with a variety of lighting conditions: during both day and night; under shade, direct sunlight, and lamplight. Bloch et al. (2021) reported 120 g accuracy and concluded that it was sufficient for cow ranking under commercial conditions. The current study obtained a higher error (MAE of 0.14 and RMSE of 0.19 kg per meal), but this error was achieved with an MV system and not a mechanical weighing system as used by Bloch et al. (2021).

Training a model with data of feed type A, followed by fine-tuning the model with data of feed type B, was superior to the rest of the models (Table 3, Table 4). In further research or commercial application, we would advise the same method in applying and utilising feed intake models for different feeds or different conditions (i.e., different illuminations, housing, species). Results suggest that our model's error was higher (MAE = 0.23, RMSE = 0.27 kg) for data collected in the afternoon comparing to the rest of the day (MAE = 0.14, RMSE = 0.19 kg for data collected in the morning-noon hours and MAE = 0.12, RMSE = 0.16 kg for data collected in the evening-night hours). Further research may consider other illumination aspects.

One of the advantages of the developed MV system is that it requires a single calibration station which enables dynamic adjustment of the model to changes in the feed mix. Tuning the model to changes in the feed mix requires less data and less training time than training a new model from scratch. Future study may examine the response time required to update the model once the feed mix is changed. Another advantage of this system is that a single computer can run multiple cameras simultaneously, collecting data from multiple feeding stations to estimate feed intake of various cows.

However, a few caveats may be noted. First, the feed in a commercial cowshed is distributed as a single unseparated long pile along the feeding lane where there is no separation between the feeding stations and therefore, the system is unable to cope with cows that eat from each other's station at the same time. Another disadvantage is the need of a single camera per feeding station. Additional research is necessary to address this issue, to decrease the total system costs (299$ per camera) by utilising a single camera in multiple feeding stations. A programmatic separation between the stations could handle this issue. Another drawback of the developed MV system is that it does not include automatic cow detection. However, this feature can be added and coupled with the feed intake system to determine how much feed each individual cow consumes.

Conclusions

Measuring cows' individual feed intake was conducted in an outdoor cowshed for multiple types of feed, at various times during the day, using newly developed machine vision and deep learning models. The selected model achieved an MAE of 0.14 kg per meal, and an RMSE of 0.19 kg per meal, for actual cows' meals automatically collected by the system installed at a research dairy farm. These results suggest the potential of measuring individual feed intake of dairy cows in a cowshed using RGBD cameras and deep learning models that can be applied and tuned to different types of feed.

Both models trained and tested using TL methods were revealed to be superior to the other models, according to the LMM and GLMM analysis (Table 4). Additionally, the TL models were more stable (i.e., had a smaller variance) when evaluating their sensitivity using 5-fold cross-validation (Table 3). The MLP-CNN model achieved a lower error than the combined model (Table 3). This demonstrates the importance of including categorical variables representing the type of feed and the image acquisition time as additional inputs to the model. Future studies should focus on adding an automatic calibration system. The system should be validated with a larger number of cameras in a commercial farm and include individual cow detection, the use of one camera for few feeding stations and development of software to handle the division of the feed lane into separate feeding stations.

Ethics approval

All the procedures in this study were carried out in accordance with the accepted ethical and welfare standards of the Israel Ethics Committee (approval number IL-801/18).

Data and model availability statement

None of the data were deposited in an official repository. The data that support the study findings are confidential.

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Declaration of interest

None.

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