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The use of animal sensor data for predicting sheep metabolisable energy intake using machine learning

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ABSTRACT

The use of sensors for monitoring livestock has opened up new possibilities for the management of livestock in extensive grazing systems. The work presented in this paper aimed to develop a model for predicting the metabolisable energy intake (MEI) of sheep by using temperature, pitch angle, roll angle, distance, speed, and grazing time data obtained directly from wearable sensors on the sheep. A Deep Belief Network (DBN) algorithm was used to predict MEI, which to our knowledge, has not been attempted previously. The results demonstrated that the DBN method could predict the MEI for sheep using sensor data alone. The mean square error (MSE) values of 4.46 and 20.65 have been achieved using the DBN model for training and testing datasets, respectively. We also evaluated the influential sensor data variables, i.e., distance and pitch angle, for predicting the MEI. Our study demonstrates that the application of machine learning techniques directly to on-animal sensor data presents a substantial opportunity to interpret biological interactions in grazing systems directly from sensor data. We expect that further development and refinement of this technology will catalyse a step-change in extensive livestock management, as wearable sensors become widely used by livestock producers.

1. Introduction

Regular monitoring of livestock managed in extensive grazing systems is essential for the animal's welfare and productivity. However, inspecting livestock routinely by direct observation or measurement is a costly and onerous task for farmers managing large herds across extensive agricultural landscapes [1]. It is widely accepted that relationships exist between grazing behaviour and feed supply. However, factors affecting this behaviour are still poorly understood, and relationships may be influenced by the characteristics of the paddock environment, flock structure and type of livestock. Livestock has been found to respond to decreased sward biomass by increasing grazing time, reducing time idling, increasing distance walked and lessening bites taken at each feeding station [2]. Sward structure also affects animal daily forage intake [3]. Thus, our understanding and use of this information are likely to benefit substantially from developments in sensor technologies and new analytical methods.

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Fig. 1 – A flock of sheep grazing a wheat stubble field in Australia.

Studies on animal behaviour using sensor technologies have emerged recently. For instance, the use of wireless technology, tracking collar, and satellite for monitoring animal behaviour can be observed in the literature [4,5]. The use of video camera and 3D accelerometers [6,7] to estimate grazing time, grass intake and grazing behaviour using sensor technologies have also been reported [2,8]. Moreover, these monitoring tools produce various forms of data, and interpretation of the data can benefit significantly from the development of suitable analytical techniques. Researchers have evaluated the potential of machine learning techniques to analyse animal behaviour data. The key to this is the development of new analytical approaches to process large volumes of sensor data into information that enables management decisions to be implemented based on animal characteristics and behaviour. Usually, the data collected are non-linear and inconsistent. To deal with this kind of data, machine learning techniques have shown to provide a better analysis [9,10]. Liakos et al. [11] stated that machine learning and especially Artificial Neural Networks (ANN) had become one of the popular methods in agricultural domains. Despite the opportunity, William et al. [12] observed that the study on livestock behaviour using machine learning and data mining approaches had been limited. Until recently, livestock researchers have worked in conventional ways such as using manual calculation and direct human observation to understand livestock behaviour. One of the reasons was the high cost of sensor devices. However, more recently, the price of sensor devices has decreased, and many researchers have realised the opportunity for using sensor data to investigate livestock behaviour. Therefore, machine learning and data mining have emerged as a potential analysis tool and some researchers have undertaken study in livestock and animal behaviour using machine learning techniques [12,13]. However, the analysis of the animal's sensor data has typically been used to classify animal behaviour, such as to assign time spent in activities such as grazing, walking, ruminating, resting or camping [12,14]. To the best of our knowledge from the literature, no model was built to provide a direct relationship between input data from sensors and the animal's metabolizable energy intake (MEI) measurement. This is, therefore, one of the primary objectives of this paper.

In previous studies, MEI was estimated using the energy content of the feed, digestibility of feed, feed intake, level of production, age, gender, and environmental conditions [15]. Therefore, MEI can be derived if diets are accurately formulated to meet weight gain targets in controlled conditions [16]. Furthermore, some other studies have measured feed intake using sensors to detect animal activities. Oudshoorn et al. [17] applied 3-axis accelerometers for detecting animal head and mouth movement to determine feed intake behaviour. Animal mouth acoustics have also been used to predict feed intake [18,19]. Another approach was carried out by Brosh et al. [20]. They studied the relationship between cows' activities such as grazing, walking, resting, and lying with energy costs. The cows were tracked by GPS collars equipped with motion sensors. The results of Brosh et al. [19] showed that the duration of the cows' activity and its distance moved correlated with the measured conditions of the pasture, such as herbage Metabolisable Energy (ME).

However, in this study, we estimated the animal's (sheep) energy intake based on established relationships between measured changes in the animal's body weight and its energy requirements, these were then related to animal grazing behaviour and the activities recorded by the sensors. Deep Belief Network (DBN) was used to analyse sensor data to directly predict MEI, which in the conventional approach was derived from measurements of livestock live weight and rate of weight gain. As DBN has not been used widely in the agriculture area, it is one of the purposes of this paper to investigate the possibility of using DBN for such prediction. Furthermore, we also addressed the problem of identifying the most important independent sensor derived variables for predicting the MEI. A Random Forest technique was applied to the six selected variables of our dataset, i.e. ambient temperature, changes in pitch of the animals' neck associated with head movements (Δpitch angle), side to side neck movement (Δroll angle), distance, speed and daily grazing time for determining the importance of the predictors.

The objectives of this study were (i) to test the hypothesis that machine learning, in particular, DBN analytics, can predict the energy intake of sheep grazing a wheat crop residue directly from the animal mounted sensor data, and identify a sensor data derived signature associated with the depletion of the feed supply from the paddock and (ii) to identify which sensor data variables are more important in predicting the energy intake. Informing the question of which variables have more influence in predicting the MEI result is an essential step toward developing a monitoring tool that would alert livestock managers when the feed supply of grazing animals is low. Our study contributes to the understanding of animal behaviour through sensor data in relation to the animals feeding conditions, and the prediction of energy intake.

2. Materials and methods

Data for this study were taken from a previous field experiment that was conducted near Tammin (31°30′19.13″S, 117° 33′33.82″E) in the mixed cropping and livestock farming region of southern Western Australia. The average daily temperature was 27.6 °C with a maximum of 45.6 °C, and a minimum of 9.6 °C during the experiment.

The sheep were grazed in an 88-ha paddock containing wheat crop residue (stubble) for 55 days, from 31 January to 25 March 2008 (see Fig. 1). Four sheep were selected randomly, namely animal ID280, animal ID285, animal ID286, and animal ID291, and GPS tracking collars (model: WildTrax, manufactured by Bluesky Telemetry™ Ltd, Aberdeen, Scotland UK) were attached to their necks (see Fig. 2). The tracking collars recorded their position and activities (roll and pitch angle) at 5-minute intervals.

The number of sheep in the flock that were fitted with sensors was relatively small, owing to the price of the sensors at that time, similar to other early livestock monitoring research [21]. Further, only data from three sheep were available for our analyses because one device was defective. Anderson et al. [22] stated that more research is still needed on what the adequate number of the data sample is, but this would vary widely depending on the nature of the hypotheses tested. For example, studies on the effect of transferring a watering-place on the home range were performed by Sugimoto et al. [23], where two cows were used to find out their grazing and drinking behaviour. A similar study was conducted by Mansbridge et al. [24], where six sheep were selected using stratified random sampling from a flock of 140 animals. In our experiment, an additional subset of 20 sheep was weighed weekly, including the four with tracking collars. At all times, the sheep had access to water ad libitum from a single dam located in the paddock. The sheep weighed 62 kg on average and were aged 4.5 years at the commencement of the study.

Australia's Commonwealth Scientific and Industrial Research Organization (CSIRO) Floreat Laboratory Animal Ethics Committee approved the protocol for the experimental work undertaken and monitored the welfare of the animals (organisational approval reference #0715).

2.1. *Data collection*

Two sets of field data were used in this study, namely sheep weight and sheep monitoring datasets. The first dataset (sheep weight) included eight weeks of the weight measurements of the sheep recorded every week. The second dataset (sheep monitoring) included data collected from the electronic collars (i.e. sensors) of three sheep (monitoring data of the fourth sheep was not suitable to be used due to a high proportion of missing data). The second dataset had 27 variables and time-stamped attributes, including data on the sheep's location. However, only five attributes related to the sensor information on animal activities, i.e. ambient temperature, Δpitch, Δroll, distance and speed, were used in the DBN analysis. Distance and speed were derived from the animals' location.

The importance of distance and speed variables can be found in some previous studies on animal behaviour. Weber et al. [25] have employed distance and speed variables obtained from GPS tracking collars. The variables were used to recognise the grazing behaviour of sheep related to the presence of livestock guardian dogs in the paddock. Other

Fig. 2 – The GPS devices used to track sheep behaviour.

variables, i.e. Angle movement (Δpitch and Δroll) variables, were related to the neck movement activities of livestock when they were active (see Fig. 3). The Δpitch (y coordinate) value measures the degrees of movement of the livestock's neck when it is rotating on the backward and forward plane while the Δroll value quantifies when it is rotating on the right and left plane. For example, the difference between the sheep is walking with the head up and grazing with the head down. The Δpitch value also detects back-forward movement associated with grazing (prehensile movements associated with biting forage). In term of this, roll angle was represented by rotation around x coordinate and pitch angle was indicated by rotation around y coordinate. For accuracy, the sensors were on the underside of the collar.

Ambient temperature values were obtained from the GPS collar, and which was local temperature from sunrise to sunset for the location.

Using latitude and longitude data collected from GPS collars, animal movement was calculated as distance and speed variable values. The distance variable value can be obtained by the Haversine formula [27]:

$$a = \sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos\varphi 1 \times \cos\varphi 2 \times \sin^2\left(\frac{\Delta\lambda}{2}\right) \quad (1)$$

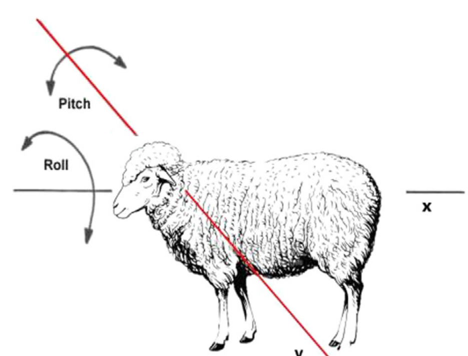

Fig. 3 – Two angle definition: Roll and Pitch angle [26].

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$$c = 2 \times atan2\left(\sqrt{a}, \sqrt{(1-a)}\right) \tag{2}$$

$$d = R \times c \tag{3}$$

where φ is latitude, λ is longitude, R is earth's radius (mean radius = 6,371 km); φ1 and φ2 are the two latitude points that would be measured; c is the angular distance, and a is the square of half the chord length between the points. Ifi atan2 s not available, c could be calculated from

$2 \cdot \mathrm{asin}(\min(1, \sqrt{a}))$. All angle measurements are in radian units. The speed was the directional speed from an animal's recorded position to the animal's next recorded position. The variables were defined as:

$$V = \frac{d}{t} \tag{4}$$

where the distance value (d) was from the distance calculation from (3) and t (time) was the recording time interval of 5 min.

These five attributes were considered to have higher biological relevance used for livestock behaviour analysis. Another attribute was added, which is the active livestock time, where sheep were determined to be walking and grazing. Location data was collected across 24 h. However, daytime data were selected (~6 AM to 7 PM) because sheep were mostly inactive at night. During the night sheep typically stayed within a small area, camping at selected locations for extended periods. At daytime, sheep were mostly active in the early morning and late afternoon. For that reason, we restricted data used for our analyses between sunrise and sunset local time.

2.2. Measurement of MEI

Accurate estimation of MEI can be determined using actual livestock weight measurement and then performing the calculation of MEI. However, in practice, regular weight measurement is a costly and onerous task for farmers. To obtain accurate MEI values, we can use what Thomas et al. [28] had observed and calculated in their study. The daily Metabolizable Energy Intake (MEI) of the sheep was calculated based on the formula:

$$\mathrm{MEI} = \mathrm{ME}_{\mathrm{maintenance}} + \mathrm{ME}_{\mathrm{gainorloss}} \tag{5}$$

The ME maintenance value was calculated based on the prediction of the medium-sized sheep breed with standard reference ewes' live weight at maturity of 50 kg:

$$\mathrm{ME}_{\mathrm{maintenance}} = 1.42 + (0.15 \times \mathrm{animalliveweight}) \tag{6}$$

Eq. (6) is derived from GrassGro [29] predictions for a medium-sized sheep breed with a standard reference ewe live weight at maturity of 50 kg.

Furthermore, $\mathrm{ME}_{\mathrm{gainorloss}}$ was obtained by the formula:

$$\begin{aligned} Y = {} & a + b\{1 - \mathrm{EXP}(-c(\mathrm{LWT} - f)) \\ & -d/(d+e)(1 + [c\mathrm{EXP}(-(d+e)(\mathrm{LWT} - f)) \\ & -(d+e)\mathrm{EXP}(-c(\mathrm{LWT} - f))]/(d+e-c))\} \end{aligned} \tag{7}$$

where Y is $ME_{gainorloss}$ [MJ/kg LWT $\text{change}_{(kg)}$]. For weight gain, a = 51.02, b = 20.62, c = 0.056, d = 0.035, e = 0.044, f = 29.8 while for weight loss, a = 27.4, b = 11.08, c = 0.056, d = 0.035, e = 0.044, f = 29.8.

There are previous studies that try to understand the relationship between the animal behaviours and the feeding management, which contributed to the factors that impact on live weight gain (LWG) and MEI. For example, Thomas et al. [30] studied MEI and animal live weight gain (LWG) intending to evaluate its potential contribution to improving feeding management practices in extensive livestock production.

2.3. The proposed MEI prediction model

There are two steps in this MEI analysis (see Fig. 4). The first step in this study was to use the sheep weight information to estimate the energy intake of the sheep throughout the grazing trial. The calculated MEI per week was obtained by using Thomas et al. [28] formula. However, the sensor data from collars were in 5-minute intervals. Due to the difference in the resolution between the calculated weekly MEI and the sensor data, we have performed interpolation to the MEI values to obtain daily MEI values.

As shown in Fig. 4, the 5-minute resolution sensor data were aggregated to daily values so that both predictors (sensor data) for MEI and the predicted MEI had the same daily time frame. The second step was to apply DBN for predicting whether there is a relationship between sensor data and the MEI values.

2.4. Pre-processing data

The sensor data from three animals, with animal ID280, animal ID285, and animal ID291, were used. A dataset from the aggregated sensor data values and the interpolated MEI values was constructed for each animal and analysed using DBN methods. The sensor data were the independent variables, and the interpolated MEI data were the dependent variables.

As indicated earlier, these two datasets had a different time resolution, the MEI values were weekly, and the sensor data were at a five-minute interval. In order to predict the energy intake of the sheep each day, all datasets were matched daily. To obtain the daily MEI values, the polynomial interpolation approach was applied to the MEI dataset. A polynomial curve was applied to create a line of best fit through the calculated weekly MEI values result. To obtain an optimal polynomial for interpolation, testing was performed by using the 2nd, 3rd, 4th, 5th, and seventh order polynomial, and the 2nd order polynomial interpolation provided the best trend line for most of the calculated weekly MEI values. The 2nd order polynomial curve was then used to interpolate the weekly MEI values to construct the daily MEI values for use as the dependent variable.

Six variables from the sheep monitoring dataset, i.e. temperature, Δpitch, Δroll, distance, speed, and grazing time were used as independent variables (predictors) after aggregation into daily values. In this analysis, we included the active livestock time from sunrise to sunset local time, where it was identified as the periods when a large majority of grazing and walking activities occur. During the experiment, the active time of the sheep was calculated for each day. For the temperature and the speed, average data values from the sensors were used for the whole day period (data available in 5-minute intervals) to represent the temperature of the day and the daily travel speed of the sheep. The sum of each of Δpitch, Δroll, and distance was used during the daytime period as the value for the day. Thus, each animal has the same number of data in one data frame, i.e. 50 rows of data with six features: temperature, Δpitch, Δroll, distance, speed, and grazing time as independent variables and one feature that is MEI measurement as the dependent variable.

To increase the number of observations in each dataset, we combine the datasets from two animals in turn. Consequently, besides the three original datasets, we used three new datasets as the results of the combinations of two datasets, i.e. animal ID280285 dataset, animal ID280291 dataset, and animal ID285291 dataset. Now in every combination of datasets, we have 100 rows of data as a result of combining two datasets.

2.5. *Training and testing data*

After the pre-processing stage, the DBN was then applied to train the dataset that consisted of the six independent variables (temperature, Δpitch, Δroll, distance, speed, and grazing time) and one dependent variable, i.e. the MEI values. DBN was first introduced by Hinton et al. [31]. It was intended to solve three problems that occur when a back-propagation algorithm is applied to deep layer Neural Network, i.e. a slow learning time, a poor parameter selection technique that leads to poor local optima, and necessity of substantially labelled data set for training [32]. The architecture of DBN was formed by a stacked Restricted Boltzmann Machine (RBM) as shown in Fig. 5.

The advantage of RBM in the pre-training process of DBN has been evaluated in some studies. Since the pre-training process (initialisation) uses RBM instead of random weight, the performance of DBN has shown in many papers to be better than conventional Neural Network. Salakhutdinov and Hinton [34], in their study, claimed that using RBM, learning would be more efficient and effective because there is no connection between the hidden units in the same layer. For the DBN, we established three main layers, i.e. input – hidden – output layers for the generation of the prediction model. Six independent variables from the sensor data were used as the input. The hidden layer consisted of three layers, and the output layer value was the MEI values.

In order to validate the proposed approach and the developed model, we have used cross-validation between animals, i.e. we will always keep the data from one animal to be used purely for testing. For example, if the training dataset was formed by combining the data from animal ID280 and animal ID285 (dataset 280285), then the testing dataset would be from animal ID291. Table 1 shows the combinations of datasets

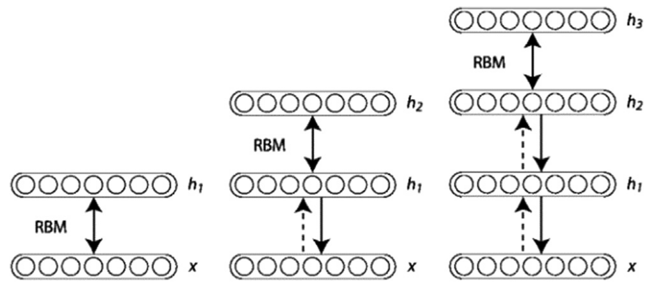

Fig. 5 – DBNs are a stack of RBM forming deep (multi-layer) architecture [33]

Table 1 – The combination list of training and testing dataset.

Training dataset	Testing dataset
Animal ID 280285	Animal ID 291
Animal ID 280291	Animal ID 285
Animal ID 285291	Animal ID 280

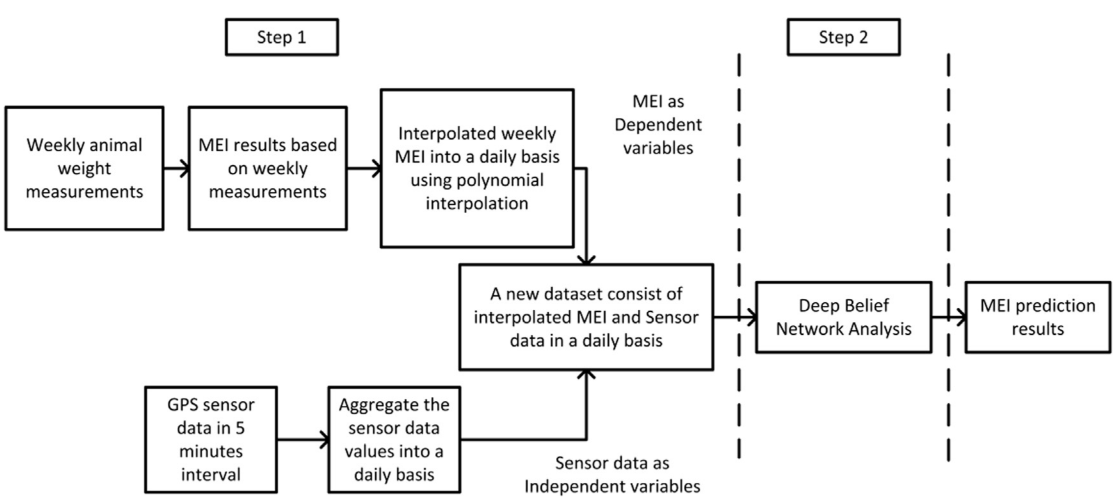

Fig. 4 – The steps in MEI analysis using DBN.

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used for the different training and testing validation cycle. We performed cross-validation by mixing all dataset into one and did re-sampling with two datasets as a training dataset and one dataset as a testing dataset (Table 1).

Cross-validation provides a measure of how good the model fit is, both for accuracy (bias), and variance. Cross-validation is applied to assess the predictive performance of the models and to find out how they work outside the sample to a new dataset. Using this method, we checked our model to determine how well the model performs against a relevant performance metric. In this case, a possible scenario is that we have several learning algorithms and just want to select the best among them by adjusting the parameters. The combined data sets are needed in cross-validation so that we do not get biased results. Ideally, we would like to see how the model performs when we have new data in terms of the accuracy of its predictions.

Next, the parameter of the DBN was selected and adjusted. Table 2 summarises the parameters of DBN that have been selected and adjusted. The best mean square error result (the smallest error value) was obtained by selecting and adjusting the predictive model parameters. In this case, we are referring to the selection of the best predictive model from the experiments that can provide the smallest mean square error by deploying the best-selected parameters. Table 2 below showed the optimal parameters used to obtain the best result of MEI.

The optimal parameters in Table 2 were obtained using the grid search method shown in Table 3.

Table 2 – DBN Parameters for training data and generating the prediction model.

Parameters	Values
Hidden layers	8 – 17 – 9
Activation function	Tanh
Learning rate	0.1
Learning rate scale	1
Momentum	0.5
Number of epochs	5000
Output function	Linear
Batchsize	10
Hidden dropout	0.1
Visible dropout	0.1
CD	1

Table 3 – Grid search method to obtain parameters values.

Parameters	values
Hidden layers	6 - 8 - 10 ; 8 - 17 - 9 ; 10 - 14 - 18
Activation function	Sigmoid ; Tanh
Learning rate	0.1 ; 0.01 Figs. 4 and 5
Learning rate scale	1 ; 0.1
Momentum	0.5 ; 0.6 ; 0.8
Number of epochs	1000 ; 5000 ; 7000
Batchsize	2 ; 6 ; 10
Hidden dropout	0.1 ; 0.4 ; 0.5
Visible dropout	0.1 ; 0.4 ; 0.5

The hidden layers, momentum, and the number of epochs were repeatedly adjusted by increasing or decreasing values in each layer to get the best result.

After training the DBN with one animal dataset to establish the prediction model, testing of the established DBN model was carried out by applying the model to the different animal dataset, which was not included in the training process, i.e. blind testing.

Furthermore, The Mean Squared Error (MSE) value was used to find the difference between the estimator and what is estimated. The MSE is calculated using the following formula:

$$MSE = \frac{1}{n}\sum_{1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{8}$$

where $\widehat{Y}$ is a vector of n prediction and Y is the vector of observed values corresponding to the input to the function which generated the predictions. Y_i is the i^{th} value of the vector.

2.6. *The variable importance analysis*

Wei et al. [35] stated that it is essential to know the more significant factor or variable in the regression or prediction analysis to be used to establish the model. Whereas Grömping [36] argued that predictive analysis would be more convincing when the most influential predictor variable obtained. To identify which variables are more significant in predicting MEI, Random Forest analysis [36] was used in this paper. The percentage of Mean Square Error (MSE) was measured by the Random Forest analysis, which indicates which variable has a more significant influence compared with other variables in predicting the MEI values. The parameters used in Random Forest analysis are shown in Table 4.

The steps to calculate the variable importance values or the increased value in MSE (%incMSE) of prediction estimated with out-of-bag-CV as a result of variable j being permuted (values randomly shuffled) are as follow. First, we computed out-of-bag MSE by creating a regression forest and name this as MSE0. Second, for 1 to j variables, permute values of column j and then predict and compute out-of-bag MSE(j). Furthermore, we determined the formula of %incMSE of j^{th} is

$$\frac{(\mathrm{MSE(j)} - \mathrm{MSE0})}{\mathrm{MSE0}} \mathrm{x}100\% \tag{9}$$

Where MSE is Mean Square Error (8) and the out-of-bag is the estimated error in Random Forest.

Table 4 – Six attributes of the independent variable were examined by Random Forest analysis to find the variable importance.

Parameters	Values
nTree	2000
Independent variable	temperature, Δpitch, Δroll, distance, speed, grazing time
Dependent variable	MEI

3. Results and discussion

Deep Belief Network (DBN), which is one of the machine learning techniques, was used to establish the prediction model of the Metabolizable Energy Intake of sheep directly from on-animal (electronic collar) sensor data. In this study, two datasets were used for training, while the third dataset was used for testing. Table 5 presents the results of experiments using different combinations of training and testing datasets.

The best result showed that by using the 2nd order polynomial interpolation, the combined training data from animal ID280 and animal ID285 (Animal ID 280285) could predict the testing data from animal ID291 better than other two combinations dataset. The MSE results were 4.46 and 20.65 for the training and testing data, respectively. All three sheep were in the same paddock. Sensors were mounted on each sheep. These sheep produced different sensor data based on the behaviour of each individual sheep. Therefore, we can observe behavioural differences between different sheep. We tested different combinations and found the combination of 280 and 285 produced the best prediction results for the third sheep. One possibility is that this combination captured the variance of the differences in the individual sheep behaviours and the machine learning technique we used can capture the underlying behaviour.

Based on Fig. 6c, in the testing data for animal ID291 we interpreted and concluded that the figure showed in the first two weeks, the feed supply was still sufficient, and therefore the MEI values increases. However, in the following weeks, the feed started to decrease so that the needs of energy intake decreased. This was depicted by the decreased in the MEI values after the first two weeks. In this controlled study, no food is resupplied in the paddock through feed supplements. When the feed supply is low, the sheep needed to travel to another area to look for feed supply or eat forage that was previously overlooked. Two reasons that the MEI values decreased are as follows. First, the overall quality of the feed was reduced as higher-quality components (such as grains) were consumed, resulting in the sheep eating poorer quality feed and cause the MEI values to reduce. Second, as food supply was reduced in a specific area, and sheep started to move in a larger area to look for new feed supply. Consequently, sheep travelled further and had a higher energy requirement. The MEI value recorded after the sheep were moved to new feed supply (a new paddock) was not measured in this study, but would be expected to return to a similar level as at the beginning of this study.

After predicting the MEI values, Random Forest analysis was carried out to observe which variable is more significant in predicting the MEI values. It is used to select the variable importance of the six independent variables. The full list of the results is shown in Table 6.

The higher the %incMSE value, the better [37]. It means variables with the highest %incMSE is the most important variable.

From this analysis, it can be observed that the MEI value is mostly affected by the distance variable followed by the Δpitch variable. Therefore, the most influential variable is distance. Grazing ruminants walk many kilometres each day to cover adequate grazing sites so that they can meet their energy requirements. Umemura [38] revealed that there is a linear correlation between the number of walking steps of livestock and its grazing behaviour. By recording the back-forth and right-left movement, the number of grazing bites and the number of walking steps can be estimated. However, this technique uses pedometers and requires calibration to relate the pedometer values to the number of grazing bites. Other studies by Krachun et al. [39], and Odadi and Rubenstein [40] also indicated that the livestock activities and distance walking are correlated to energy intake and live weight gain.

Moreover, the results of this study are in line with other research regarding pitch and head angles measurement to be used to estimate grazing activity [41,42]. Other studies of livestock grazing behaviour and forage intake were also implemented by analysing the jaw movement and bites count rather than on the pitch and head angles [6,17,38]. These studies revealed that jaw movement and bite count or pitch, and head degrees of angles could depict movements associated with feed intake. Therefore, these movements, while foraging was indicative of the energy intake of the animal. Our study confirmed that the pitch (Δpitch) value is a good indicator of feed intake.

We have shown that the two variables, distance and Δpitch, may be used to predict the energy intake of sheep. Our results suggest that if sheep are grazing in an area with abundant food, they may travel only a short distance initially, but then increase their activity as feed becomes less available. However, over time if the supply of feed becomes severely restricted (for example, food is depleted to a point where the sheep are not able to meet their energy intake requirements to maintain their body weight), their grazing activity decreases. Since the grazing behaviours of herbivores relate to the circumstances they encounter when foraging, we expected that this would be influenced by the ease or difficulty of meeting their energy requirements. Relationships between livestock grazing activity and the availability of feed (pasture) and their live weight have also been reported in other studies [43].

In this study, we interpolated the MEI weekly data to daily data due to the limited number of data available for MEI val-

Table 5 – Training and testing data results.

Training dataset	MSE training results	Testing dataset	MSE testing results
Animal ID 280285	4.46	Animal ID 291	20.65
Animal ID 280291	15.62	Animal ID 285	173.49
Animal ID 285291	9.88	Animal ID 280	64.04
Average MSE	9.98		86.06

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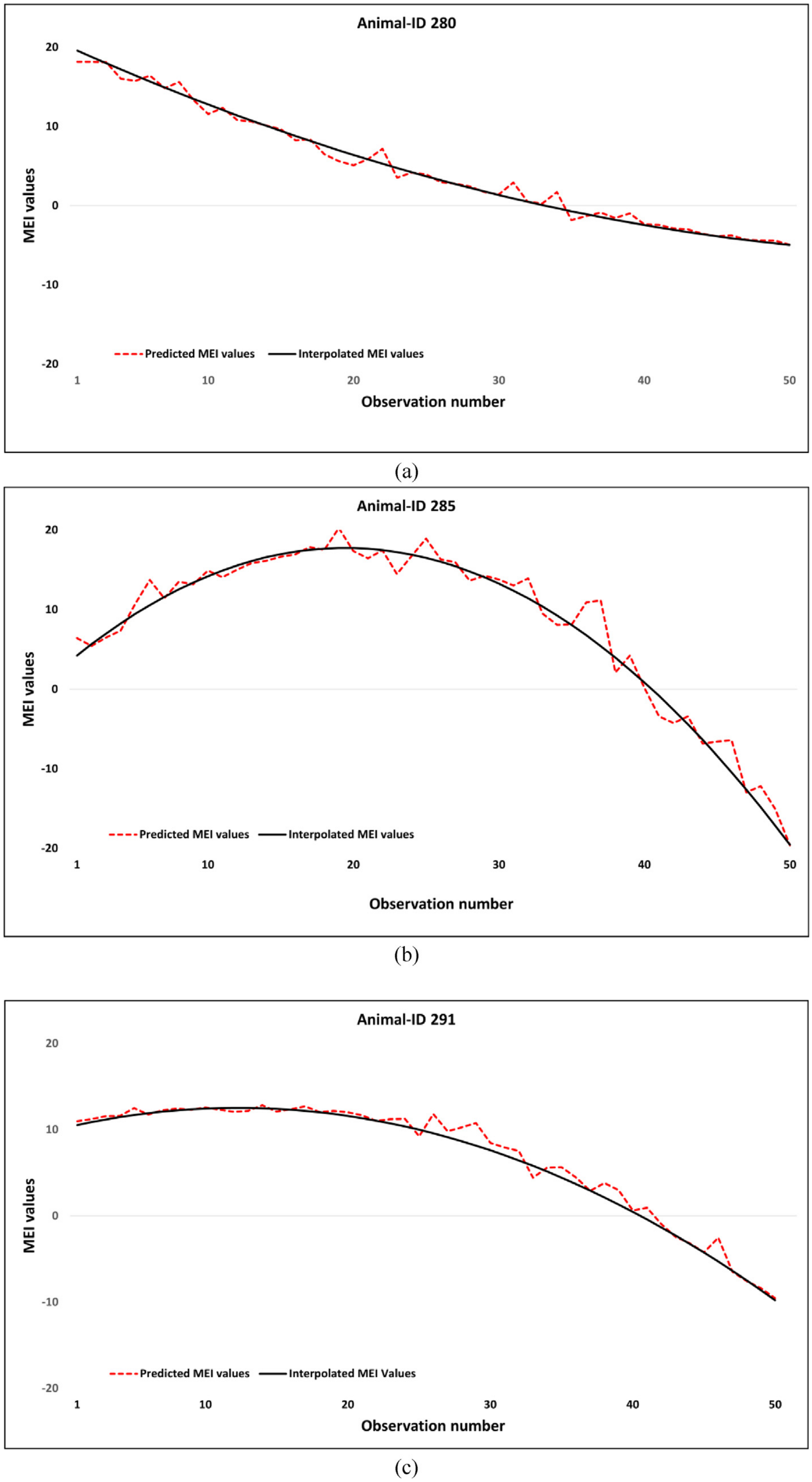

Fig. 6 – (a) The diagram of the best MSE result of the animal ID280 training dataset, (b) The diagram of the best MSE result of the animal ID285 training dataset, (c) The diagram of the best MSE result of the animal ID291 testing dataset.

Table 6 – Variable importance results.

Variables	MSE values (%)
Distance	37.22
ΔPitch	34.65
ΔRoll	28.23
Grazing time	28.01
Temperature	26.87
Speed	13.24

ues, derived from the weekly weighing of sheep in the field for the duration of the study. Interpolation is necessary for this research and can also be observed in other research when exact values are not available, and we need to convert from weekly data to daily data before any regression analysis type work can be performed [44]. The interpolation of geolocation data has been used previously in an animal tracking study in a fluid environment [45]. They observed albatrosses, penguins, boobies, sea lions, fur seals and elephant seals tracking data and used six mathematical algorithms to interpolate animal tracking data. As a result, they recommended using curvilinear interpolation techniques. They also provided the guidelines for choosing the algorithms for different types of marine vertebrates.

The use of the interpolation data to get the higher resolution data showed that in term of machine learning algorithms, the number of data is crucial [46,47] even though Hilbert [48] argued that not only the number of data but also the selected algorithms could affect the accuracy of the prediction results. Dealing with this constraint, Morota et al. [49] showed that the use of fully automated devices, high-throughput data recording including digital images, sensor and sound data, unmanned systems and information obtained from real-time non-invasive could increase the accuracy of the prediction. As has been mentioned previously, the solutions suggested the use of a walk-over weighing systems to obtain the higher resolution live weight data. According to Aldridge et al. [50], the systems could be considered as a tool for improving the resolution and number of data.

4. Conclusions

Determining the energy intake of grazing animals has been a long-held ambition of researchers and livestock managers alike. This new research approach provides a major opportunity to overcome this problem. It is common to estimate metabolisable energy intake, based on the amount and quality of pasture and supplements that are offered to livestock. However, in this study, we predict the MEI value directly from wearable sensors using a machine learning method. The findings that we have presented demonstrates the successful use of sensor data, i.e., pitch, roll, distance, speed, temperature, and grazing time to predict the MEI of sheep. We have also identified the sensor data variables that were the most influential in predicting the MEI value, being distance and pitch. Based on this, we expect this model is suitable to be applied to new sensor data with the same variables. However, to get the best model performance, the model parameters should be tested and re-trained for any new datasets to ensure the new grazing conditions are adequately represented.

Our research demonstrates that with the aid of modern sensor technology, quantifying the energy intake of grazing animals is now possible, which has the potential to catalyse the next generation of precision livestock management resulting in improvements in both welfare and productivity outcomes, as we have discussed. By predicting the MEI using sensors data, the cost and need for human intervention to estimate energy intake may be considerably reduced. With knowledge of when the MEI value starts decreasing below a significant threshold, the livestock manager could plan more effectively to provide a new grazing location to better meet live weight targets for the livestock.

In future studies, addressing the variability among individual animals and the opportunity to use alternative behaviour measures remains an open and active research topic. Moreover, this study could be used as the development of the machine learning algorithm by implementing the model in different grazing systems or using data from one flock to predict similar patterns in sheep in a completely different flock to reveal the underlying factors in predicting the MEI value. Given the current issues in climate change and environmental sustainability, improving our ability to observe and understand behaviours expressed in extensive livestock systems will also provide an important area of application for this research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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