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A Deep Learning Approach-FDNN: Forest Deep Neural Network to Predict Cow's Parturition Date

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Abstract: In this prospective study, we integrate neural network architecture with a supervised random forest feature detector to develop a new model named Forest Deep Neural Network (FDNN) to predict daily and hourly calving time of cattle. To overcome challenges of prediction problems like data sparsity along with unknown correlation structures, we incorporate the benefits of random forest (RF) with a deep neural network (DNN) to predict the daily and hourly calving time of cattle, which is nobody done yet. For this study, we take a total of 45 Holstein-Friesian cows (27 primiparous and 18 multiparous) for collecting physical activities. Using IceQube and HR Tag technologies, we record daily and hourly lying time, the number of stand-ups, ruminating time, the number of steps, and the number of head moves of cattle from 15 days before the actual calving time. Different statistical analysis has been carried out over the daily and hourly-captured data, and we have found that these monitored physical activities change very significantly over time. We have applied five classifiers such as FDNN, DNN, RF, decision tree (DT), and support vector machine (SVM) over the daily and hourly datasets. Hyperparameter optimization has been conducted over the classifiers using Grid Search approach to filter out the optimal parameter configurations. With optimal parameters, our developed model overpowered the other four classifiers in terms of accuracy, sensitivity, specificity, and ROC score (ACC= 98.38, SN=88.19, SP=98.41, and ROC=99 of predicting daily calving time; ACC=97.93, SN=97.40, SP=89.42, and ROC=98 of predicting hourly calving time).

Keywords: calving time; random forest; deep neural network; forest deep neural network; model optimization

1. Introduction

Parturition accident is a very common and serious problem for dairy farmers. It is expected to maintain a good care of living calves in order to drive the economy as well as animal welfare [1]. In Bangladesh, the calf mortality rate is higher than 36.87 percent, in which 11.7 % calf mortality occurs due to parturition accident, commonly known as dystocia [2], [3]. This accident could lead to the death of a child-occupied cow that results in a reduction of milk yield. Keeping timely observation on laboring cattle with proper calving assistance may reduce the risk of dystocia and pain associated with labored cows, and improve reproductive performance in the subsequent lactation [4], [5]. Keeping close observation in open eyes is laborious and quite hard as there is no visible indication of when a cow is bound to give birth. Besides, food intake plays a significant role to change the important indicative signs of calving, Which makes also harder for a farmer to predict the time of actual calving [6]. As it takes a tremendous effort to oversee indications, dairy farmers currently utilize the combination of breeding records and visual cues to estimate probable calving time. Using conventional approaches, dairy farmers may not determine the calving time accurately as the physical activities of some cows do not change consistently across the calving [7].

To overcome these issues of determining probable calving time by overlooking visual clues, dairy farmers use a precision dairy monitoring technologies that are consisted of maternal body-temperature monitors [8], [9]. This technology provides an alternative of observing visual signs in open eyes by measuring maternal body-temperature as it changes significantly with the passes of gestation time [10]. Researchers found that the maternal body temperature is decreased significantly from 48 hours before probable calving [11]. The dairy farmers use different technologies for measuring vaginal temperature, skin temperature, and reticulorumen temperature, but none of these have found validated for estimating calving time [12]. A study was conducted to quantify the changes of vaginal and rectal temperature of cattle when calving approaches, and they predicted the calving time by analyzing these behaviors with specificity ranging from 81% to 87%, and sensitivity ranging from 62% to 71% [13]. Besides, the insertion of monitors for measuring the vaginal temperature at the second stage of calving has been banned. Hence, the necessity of an alternative to these technologies has been intensified, and leads to develop technologies for monitoring physical activities.

Subsequently, calving time prediction using behavioral activities such as ruminating time, steps, standing time, lying time, and lying bouts (LB) has become very popular, and found more effective in this regard than the previous technologies [14]. To summarize the effects of calving on behavioral changes, an attempt was taken where found a significant increase in the number of steps and standing time, a notable decrease in lying time and short lying bouts before 24h of calving in compared with day −4, −3, and −2 [15]. Different technologies such as IceQube (IceRobotics Ltd., Edinburgh, UK), HR Tag (SCR Engineers Ltd., Netanya, Israel), DVM bolus (DVM Systems LLC, Greeley, CO), CowManager SensOor (Agis Automatisering, Harmelen, the Netherlands), and Track a Cow (Animart Inc., Beaver Dam, WI) have been used for monitoring physical activities of cattle [7], [16]. The data collected from these individual devices have been monitored separately and jointly to determine the date of calving. Initially, various researches have been carried out using different statistical approaches to figure out changes in behaviors, and predict actual calving time [17]. Statistical models are designed for identifying the relationship, and correlation among variables. Some statistical models are able to make predictions, but the accuracy of these models is not satisfactory. Different descriptive and inferential statistical analyses such as linear regression, logistic regression, and linear mixed model etc. have been applied over the collected data to make some useful predictions [18], [19].

It is known that whereas the predictive power of statistical models is not so strong, the uses of these models have been replaced with a newer approach called machine learning [20]. Machine learning is an application of AI (artificial intelligence) that enables the system to learn and improve knowledge from data, in which the knowledge is used to predict and classify data [21]. A good number of supervised machine learning algorithms such as random forest (RF), decision tree (DT), support vector machine (SVM), k-nearest neighbor (KNN), and convolutional neural network (CNN) etc. have widely been used for solving various classifying and prediction problems of dairy cattle

[19], [22], [23]. Few works on predicting calving time of cattle have been carried out using these classifiers. Although these algorithms have classified and predicted the calving time more accurately than the previous technologies, the accuracy doesn't seem as reliable as we expected. These models are found less efficient when the data are independent, and data sparsity presents among the data [24]. Besides, effective data pattern extraction is not possible using these classifiers when the length of the given input is long. To overcome these limitations of these classifiers, another form of artificial neural network (ANN) with multiple layers known as deep neural network (DNN) has been developed, and widely used in different prediction and classification problems [25]. Although the DNN has great predictive power, it has less feature extraction capacity. Additionally, the RF classifier has great feature extraction capacity while it has less predictive power in some circumstances [26]. Hence, it can be hypothesized that the combination of a feature extractor RF classifier and a learner-predictor DNN will outperform all other state-of-the-art models of cattle calving prediction.

The problems associated with the existing technologies of calving prediction, and the combined power of RF and DNN have motivated us to develop a model for predicting calving time by analyzing their physical activities such as the lying time, the number of stand-ups, the ruminating time, the number of steps, and the number of head moves. In this study, we have developed a novel model named as Forest Deep Neural Network (FDNN) by combining the power of RF and DNN for calving time prediction. The physical activities on daily and hourly-basis have been collected using two technologies such as IceQube (IceRobotics Ltd., South Queensferry, UK), and HR Tag (SCR Engineers Ltd.). We have performed different statistical analyses to quantify the changes of physical activities when the calving time approaches. In order to obtain the highest performance of our developed model, we have also performed hyperparameter optimization using Grid Search algorithm. We have used five-fold cross-validation technique instead of splitting training-testing data to evaluate performance of our model. In later, the daily and hourly prediction accuracies of our model have been compared with that of four other classifiers like RF, DNN, DT, and SVM. We also have carried out some other comparative analyses in order to expose where our model performs better and where not.

The rest of the paper is divided into three sections. The first section outlines the materials and methods of this study. The obtained results are presented and discussed in the second section while our conclusions with future works are drawn in the last section.

2. Materials and Methods

2.1. Data Collection:

The study has been carried out on AB farm located at Chattogram, Bangladesh between April 2019 and December 2019. A total of 45 Holstein-Friesian cows (27 primiparous and 18 multiparous) have been considered for this study, in which the mean age was 3.7 ± 0.88 years (mean ± SD), the mean parity was 1.4 ± 0.6, and their gestation length was 281 ± 5 days. Cows are moved to dry cow facilities before 50 days of probable calving in order to capture non-biased data. To capture lying time, number of stand-ups, and number of steps of each sample cow in each 15 minutes, we have fitted the IceQube (IceRobotics Ltd., South Queensferry, UK) at rear leg of cow from 50 days before the predicted calving. The IceQube is an accelerometer-based device that measures acceleration and orientation multiple times per second across three axis. Another device named as the HR Tag (SCR Engineers Ltd.) is placed at left side of neck of each cow that has collected number of head movements and ruminating duration in every 2 hours period. The HR Tag utilizes the benefits of three-axis accelerometer and a microphone with a microprocessor to capture number of head movements and ruminating duration respectively. For performing the experiments, we have considered the data of 15 days before the expected calving date. We have checked the health condition of each cow in every week in order to ensure healthy sample during the period of data collection. We have generalized the collected data in two ways-one was daily basis while another was hourly basis. These two different datasets are used to evaluate the performance of our developed model.

2.2. Statistical Analysis:

Physical behaviors of cow change significantly with the passes of time during pregnancy. When the calving period is getting closer, the changes become more evident. We performed several statistical analyses to quantify the changes in behaviors like the lying time, the number of stand-ups, the ruminating time, the number of steps, and the number of head moves. We have collected data in every day and hour, and analyzed to find out the significance of each behavior to determine the outcome. Since we have data from more than one source, and the outcome has taken by repeated measures over time, we have to account both within-subject and between-subject variabilities. Besides, our data points might not be truly independent. Due to these characteristics of our data, we have applied Linear Mixed Model (LMM) to capture the fixed and random effects of parameters over the outcome [27], [28]. LMM has been applied over the data collected in both daily and hourly basis. We have tested all two-way interactions among the parameters to find out the non-significant attributes that were removed using backward stepwise elimination. All daily collected data of each cow have labeled as -1 to -15 while all hourly generated data of respective cow have labeled as -1 to -359. In order to report the changes of behaviors like lying time, number of stand-ups, ruminating time, number of steps, and number of head moves in this period, we estimated deviation from the baseline values for each cow by subtracting the hourly and daily value from that of the average value

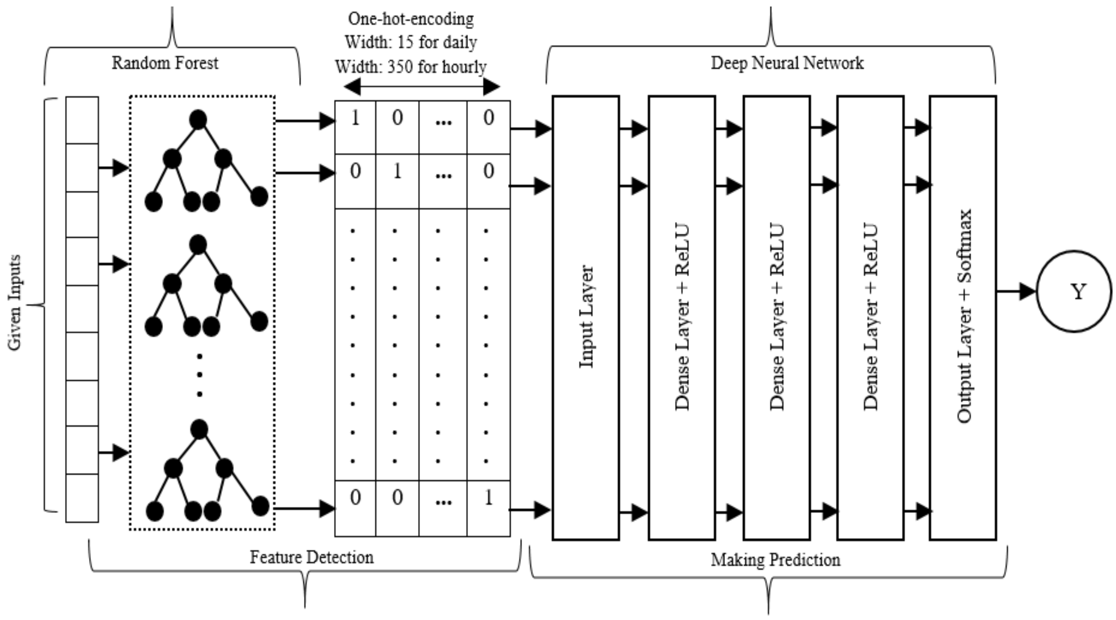


Figure 1. Architecture of our developed FDNN model for calving time prediction.

of the previous three days. Before performing LMM, residual plots were generated for each analysis to evaluate data normality, and identify possible outliers.

2.3. Model Development

In this study, we have developed a model for predicting calving time using random forest (RF) and deep neural network (DNN). We have performed hyper-parameter optimization using Grid Search (GS) algorithm, and using that optimal parameters we have obtained the highest prediction accuracy.

Forest Deep Neural Network (FDNN)

In our proposed forest deep neural network (FDNN) model, we have combined the benefits of both random forest (RF) and deep neural network (DNN). We have incorporated the forest part to serve as a feature detector from the training data, and the DNN part to perform as a learner in order to predict outcomes using new feature representations. Multiple independent decision trees have been constructed in the forest part, where each tree has produced a binary outcome. Here, outcomes of all trees are combined together, and organized in a one-hot-encoding, which are given into the DNN part as inputs. Several forest construction algorithms are available. In this study, we have employed Random Forest (RF) algorithm for detecting features from the raw inputs. The architecture of our developed model is shown in Figure 1. The width of one-hot-encoding vector is 15 for the daily prediction model, and 350 for the hourly prediction model. The generated one-hot vector is passed through three densely connected hidden layers of the DNN model.

Rectified linear unit (ReLU) is used as an activation function in the hidden layer because it can avoid varnishing gradient problem during optimization. Here, algorithm optimization has been carried out using Adam optimizer since it has widely been used in deep learning as a variant of traditional gradient descent algorithms. We also have utilized the mini-batch training strategy by which the optimizer trains small subset of input data randomly in each iteration. A Softmax activation function is used in the output layer that generates a probability distribution, and decides in which class the given input is in. In this model, training has been carried out in two phases. The labelled input data is passed through the forest part in the first phase, and outcomes from each tree of forest for all inputs are then fed into the fully-connected DNN, for training in the second phase. After completing the two-phase training, a new data is given to the FDNN model for prediction by utilizing the entire model. We have used five-fold cross-validation technique for evaluating training and testing performance of our model. The configuration of layers is shown in Table 1.

Table 1. Layer shape of DNN parts of the FDNN model.

Layer (type)	Output Shape	Parameters
Input	0	0
Hidden-1 (Dense)	(None, 128)	12800
Hidden-2 (Dense)	(None, 256)	33024
Hidden-3 (Dense)	(None, 256)	65792
Output (Dense)	(None, 1)	257

Performance of a machine learning algorithm highly depends on the optimum values of parameters. The optimum values of parameters are obtained by tuning with different values, and observed performance where the algorithm returns better accuracy. Hyper-parameter optimization also known as hyper-parameter tuning is the problem of selecting a set of optimal parameters that lowers the cost function of the model [29]. We have performed hyper-parameter tuning over the forest and DNN parts of our model. Grid search, also called exhaustive search, looks through each combination of hyper-parameters using permutation and combination [30]. The performance of grid search algorithm is measured using cross-validation on the training set or evaluate on a held-out validation set. After performing all possible combinations of hyper-parameters, the grid search algorithm returns the settings that achieved the highest accuracy in the validation process along with the obtained accuracy. Hyper-parameter optimization of RF and DNN are performed by keeping the value of these parameters respectively as follows:

RF: [n_estimator=64, 100, 128], [max_features =auto, sqrt, 0.2], [min_samples_split = 2, 5, 10], [min_samples_leaf = [50, 100, 150]]

DNN: [learning rate=0.01, 0.03, 0.05], [batch size=16, 32, 64, 128], [hidden units=50, 100, 150], [epoch=200, 250, 300, 350]

After performing hyperparameter optimization, grid search algorithm returns optimal hyperparameters along with the highest accuracy of each model. We have performed grid search algorithm over the model using GridSearchCV algorithm from sklearn package in python.

2.4. Performance Evaluation

The performance of the applied models was evaluated by measuring sensitivity (SN), specificity (SP), and accuracy (ACC). The sensitivity defines the ability of a model to accurately classify the true positive samples, while the specificity of a model is the capacity of identifying the true negative samples [31], [32]. The accuracy of a model is the number of patients correctly classified by a model. The formulas are as follows [33]:

$$Sensitivity\ (SN) = \frac{TP}{TP + FN} \tag{1}$$

$$Specificity\ (SP) = \frac{TN}{TN + FP} \tag{2}$$

$$Accuracy\ (ACC) = \frac{TN + TP}{TN + TP + FP + FN} \tag{3}$$

The true positive (TP) specifies the number of classified positive patients those are actually positive. True negative (TP) represents the number of predicted negative patients who are actually negative. False positive (FP) is the number of classified positive patients who are actually negative. And false negative (FN) specifies the number of identified negative patients who are actually positive. We also have plotted the Receiver Operating Characteristic (ROC) curve that compares the true positive and false positive rates of applied models. These parameters are often estimated to assess the classification quality of models.

3. Results and Discussion

The study is designed to develop a machine learning model that isbased on Forest Deep Neural Network (FDNN) in order to predict calving time of cattle by analyzing their physical activities like lying time, number of stand-ups, ruminating time, number of steps, and number of head moves. The performance of our FDNN model is compared with that of the random forest (RF), deep neural network (DNN), decision tree (DT), and support vector machine (SVM) classifiers. Data have been

Table 3. Adjusted LSM (± SE) from daily linear mixed models that captures interaction between parity and physical activities of 15 days prepartum period before calving.

Days	Lying time (m/d)	Stand-ups (n/d)	Ruminating time (m/d)	Steps (n/d)	Head moves (n/d)
-15	1067±98.21	159±32.21	386±29.32	1697±61.42	965±51.25
-10	1021±61.41	167±40.11	367±45.65	1631±79.28	971±47.65
-8	942±68.25	169±25.36	341±78.32	1762±68.45	989±34.58
-4	867±95.31	178±24.12	281±12.32	1761±41.36	993±61.32
-2	764±42.87	181±19.68	242±41.36	1898±54.21	1049±45.67
-1	589±57.21	185±27.37	139±51.32	1967±70.32	1121±37.48
-0	437±34.98	221±14.10	78±43.21	2089±68.32	1203±49.18
P-value	**.012**	**.031**	**.014**	**.001**	**.001**

collected from 45 Holstein-Friesian cows by using two different- IceQube (IceRobotics Ltd., South Queensferry, UK), and HR Tag (SCR Engineers Ltd.). Two different datasets, one is based on daily data, and another is based on hourly data, are generated for evaluating the performance of our model. In order to filter the characteristics of physical activities, we have performed linear mixed effect analysis on the both datasets that are shown in Table 2 and Table 3 respectively. We have observed interactions between parity effects and daily-hourly physical activities. We have found significant interactions between parity and daily physical activities as shown in Table 2 ($P<0.05$). We have also

Table 2. Adjusted LSM (± SE) from hourly linear mixed models that captures interaction between parity and physical activities of 72 hours prepartum period before calving.

Hours	Lying time (m/h)	Stand-ups (n/h)	Ruminating time (m/h)	Steps (n/h)	Head moves (n/h)
-72	39±11.87	16±6.47	28±13.85	69±12.21	39±7.61
-48	37±9.45	15±10.69	25±8.69	63±10.24	36±10.01
-24	32±7.68	13±12.35	24±14.28	59±14.08	30±9.48
-12	30±9.39	10±8.70	18±11.05	56±11.69	25±11.36
-8	28±10.25	9±9.76	12±10.75	55±12.74	28±13.78
-4	27±11.78	6±5.89	9±13.01	71±9.68	33±11.90
-0	22±11.47	13±6.59	5±5.78	92±14.67	42±14.36
P-value	**.037**	**.024**	**.001**	**.002**	**.001**

reported interactions of parity with hourly physical activities ($P<0.05$) as shown in Table 3. The importance of each physical activity to predict daily and hourly calving time is also analyzed. Table 2 shows that the respective P-value of 0.012, 0.031, 0.014, 0.001, 0.001 of physical activities like lying time, number of stand-ups, ruminating time, number of steps, and number of head moves are less than 0.005, which indicates the importance of each activity over the prediction of daily calving time. According to Table 3, hourly physical activities have significant impacts over predicting hourly

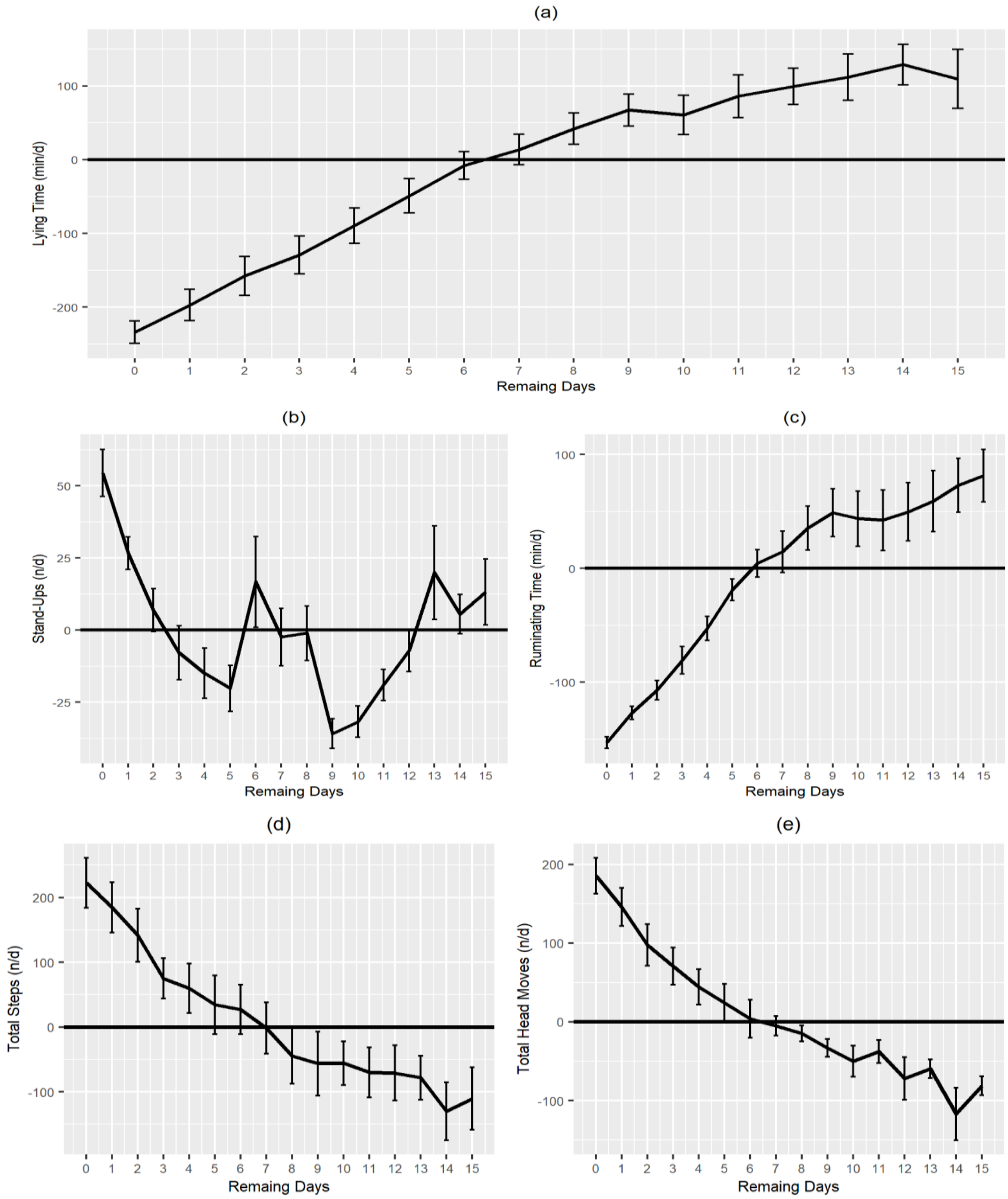


Figure 2. Changes of physical activities over the day. (a) Lying time, (b) Total stand-ups, (c) Ruminating time, (d) Total steps, (e) Total head moves.

calving time as P-value of each activity is less than 0.05. Behavioral changes of cattle on daily and hourly basis are depicted in Figure 2 and Figure 3 respectively. Daily lying time is decreased constantly throughout the period. The highest lying time is observed at the14th day before calving while the lowest is found at the actual calving day (Figure 2(a)). Likewise, hourly lying time is decreased till 28 hours before calving, and found some significant ups and downs in the later time scale until the actual calving happened (Figure 3(a)). Number of stand-ups per day are found high at early stage and actual day of calving while the lowest are observed in the middle (Figure 2(b)). Hourly stand-ups are decreased from the 72 hours before actual calving, and found the lowest at the 40th hour before calving while the highest hourly stand-ups activity is observed at the actual calving

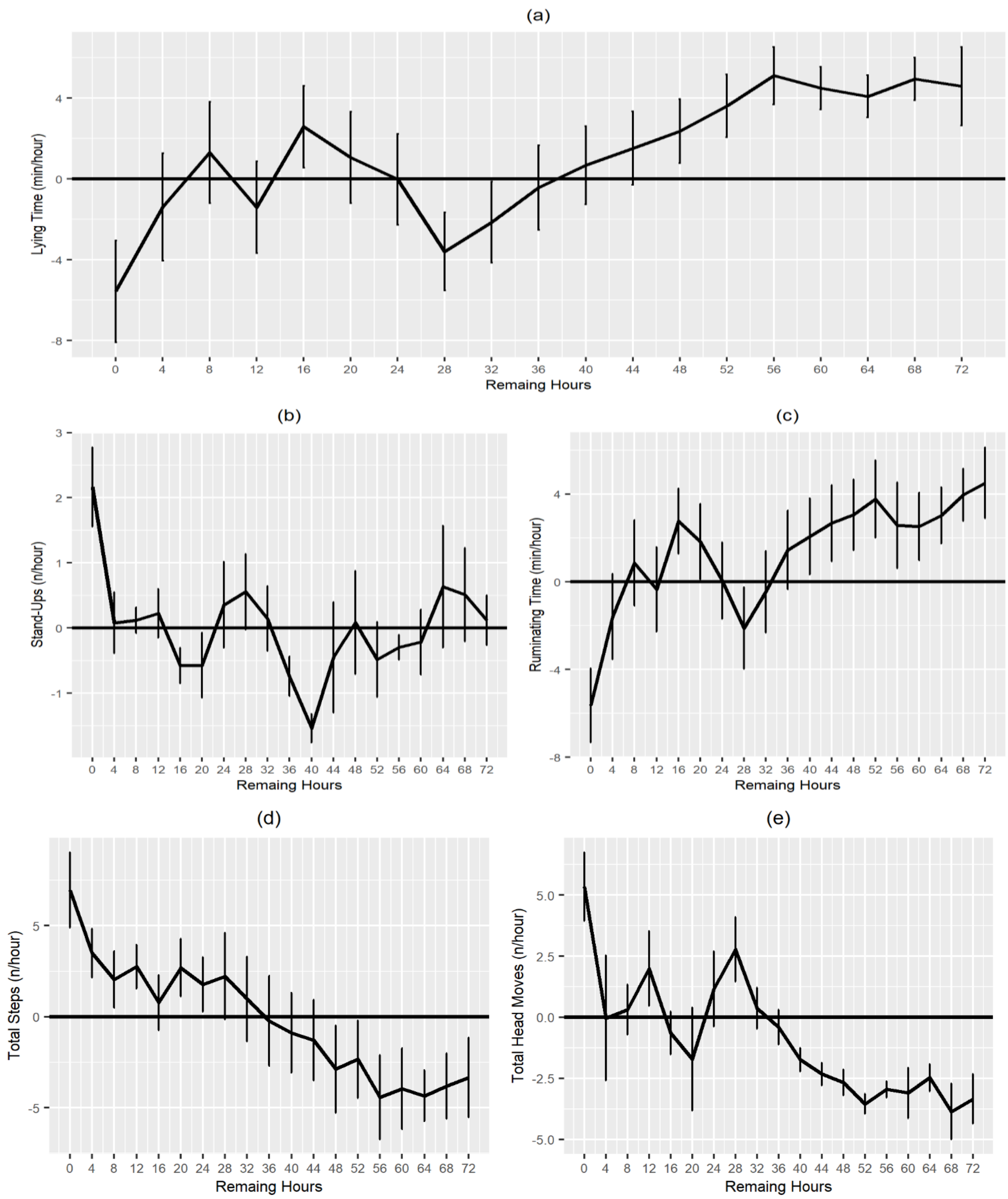


Figure 3. Changes of physical activities over the hour. (a) Lying time, (b) Total stand-ups, (c) Ruminating time, (d) Total steps, (e) Total head moves.

day (Figure 3(b)). The observation from ruminating time on daily and hourly basis expresses that daily ruminating time is decreased over the day (Figure 2(c)) while slight increase is found in the middle of hourly period (Figure 3(c)). Number of steps per day and hour are increased with time. The lowest value of the total steps are reported at the 15th day before calving while the highest at the actual calving day (Figure 2(d)); the lowest total steps are found at the 72nd hour before calving while the highest at the actual calving hour (Figure 3(d)). We have found a linear increase in the total number of head moves per day from 15 days before calving to the actual day of calving (Figure 2(e)). Similarly, hourly head moves are also increased over the hour, but slight ups and downs is found in the middle (Figure 3(e)). All these comparison signifies that the changes of lying time, stand-ups, ruminating time, total steps, and total head moves per day and per hour are found significant to predict the calving time.

A machine learning model has been developed by combining Random Forest (RF) and Deep Neural Network (DNN) to predict daily and hourly calving time of cattle. This model represents an innovative alternative that overcomes the limitations of other models. For each of the two datasets, we have used five-fold cross-validation technique to train and evaluate the model. Hyper-parameters are chosen by using Grid Search approach. The results of hyper-parameter optimization for daily and hourly calving prediction are shown in Table 4 and Table 5 respectively. The combination of best

Table 5. Hyper-parameter optimization of FDNN model for daily calving prediction.

Random Forest				
n_estimator	max_features	min_samples_split	min_samples_leaf	Mean test score
64	0.2	5	100	98.91
100	auto	5	100	96.79
100	sqrt	10	150	95.09
DNN				
Learning rate	Batch size	Hidden units	Epoch	Mean test score
0.01	64	100	250	97.86
0.01	32	150	250	96.58
0.03	32	100	250	96.01

three hyper-parameters of each part of our developed model is presented there. Table 4 shows that for daily prediction model, the RF classifier part has achieved the highest mean test score of 98.91 percent with parameters of n_estimator of 64, max_features of 0.2, min_samples_split of 5, and min_samples_leaf of 100. The DNN part has returned the highest mean test score of 97.86 percent with the configurations of learning rate of 0.01, batch size of 64, hidden units of 100, and epoch of 250. Table 5 shows that RF classifier with the configurations of n_estimator of 100, max_features of sqrt, min_samples_split of 5, and min_samples_leaf of 100 has achieved the highest mean test score of 98.08 percent, and DNN classifier has obtained the highest mean test score of 98.32 percent with the parameters of learning rate of 0.01, batch size of 32, hidden units of 150, and epoch of 250.

Table 4. Hyper-parameter optimization of FDNN model for hourly calving prediction.

Random Forest				
n_estimator	max_features	min_samples_split	min_samples_leaf	Mean test score
100	sqrt	5	100	98.08
64	0.2	5	150	97.46
64	sqrt	10	100	99.17
DNN				
Learning rate	Batch size	Hidden units	Epoch	
0.01	32	150	250	98.32
0.03	64	100	250	97.10
0.03	64	100	250	95.87

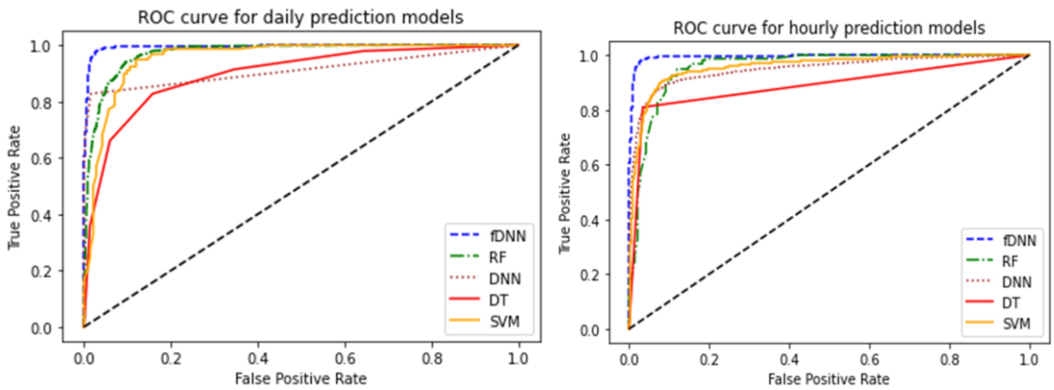
With optimal parameters, the final FDNN, RF, DT, and SVM models have been applied over the two datasets. The performance of these models are evaluated by estimating sensitivity, specificity and overall accuracy. The accuracy of these models for predicting daily and hourly calving time is shown in Table 6. For predicting daily calving time, the FDNN model has outperformed the other four classifiers. The FDNN model has predicted daily calving time with accuracy of 98.38 percent. It also has classified positive and negative cases with 88.19 and 98.41 percent accuracy respectively.

The ROC score of 99 percent of our FDNN model is higher in compared to that of other models. In contrast, the lowest accuracy, sensitivity, specificity, and ROC score for daily calving prediction are obtained by SVM classifier, which are 82.39, 71.36, 65.84, and 81 percent respectively. The FDNN model also has overpowered the other four models in terms of accuracy, sensitivity, specificity, and ROC score for predicting hourly calving time. The accuracy, sensitivity, specificity, and ROC score of our model are 97.93, 97.40, 89.42, and 98 percent respectively whilst the lowest accuracy (81.68), specificity (81.01), sensitivity (78.32), and ROC score (82) are obtained by the SVM classifier. The reason behind the lower performance of SVM classifier is data sparsity that curbs to generalize the new data effectively. After all, Table 6 signifies that in both cases, our developed FDNN model has showed the better performance for predicting calving time. In our opinion, some factors like combination of RF with DNN that has allowed us to capture data pattern effectively, and hyperparameters optimization could well be responsible for this better performance of our model.

Table 6. Accuracy of calving time prediction of different models over daily and hourly data.

Prediction Type	Models	Accuracy (ACC)	Sensitivity (SN)	Specificity (SP)	ROC score
Daily Prediction Model	RF	86.73	71.65	82.34	95
	DNN	88.31	82.43	95.05	91
	DT	85.98	72.14	84.68	85
	SVM	82.39	71.36	65.84	81
	FDNN	**98.38**	**88.19**	**98.41**	**99**
Hourly Prediction Model	RF	90.67	91.72	88.02	97
	DNN	91.68	81.10	92.41	92
	DT	86.47	82.16	72.64	87
	SVM	81.68	78.32	81.01	82

The ROC curve of these models for predicting daily and hourly calving time is shown in Figure 4. The ROC curves also indicate the superiority of our developed FDNN model over the other four models. To the best of our knowledge, no other authors have found such good accuracy to predict cattle calving time. It is plausible that a number of limitations like small dataset might have influenced the results obtained. The performed experimental analysis confirms that the correlation between physical behaviors of cattle and calving time is worth noting. The changes found in physical behaviors of during this experimental time are in line with previous results [11], [34]–[36]. The aforesaid depiction has led us to conclude that the model with combination of RF and DNN named



(a) (b)

Figure 4. Receiver Operating Characteristic (ROC) curve of FDNN, DNN, RF, DT, and SVM classifiers. (a) Daily calving models, (b) Hourly calving models.

as Forest Deep Neural Network (FDNN) has outperformed the state-of-the-art models of calving time prediction.

4. Conclusion

The study has been conducted to develop a deep learning model named as Forest Deep Neural Network (FDNN) by combining the benefits of random forest (RF) and deep neural network (DNN) for predicting daily and hourly calving time of cattle. Our research underlines the importance of effective data pattern extraction that has been accomplished by incorporating RF with DNN. A novelty of this study is combining the two classifiers together to perform classifications and predictions. A total of 45 Holstein-Friesian cows (27 primiparous and 18 multiparous) are considered for this study, from which lying time, number of stand-ups, and number of steps of each sample cow in every 15 minutes are captured by using the IceQube (IceRobotics Ltd., South Queensferry, UK) at rear leg of cow from 50 days before the predicted calving. Another device named as the HR Tag (SCR Engineers Ltd.) is placed at left side of neck of each cow that records number of head movements and ruminating duration in every 2 hours period. Two different datasets are established, and five classifiers namely FDNN, DNN, RF, decision tree (DT), and support vector machine (SVM) are applied over them. Linear mixed model analysis has been carried out to explore the behavioral changes of cattle before the actual calving bound to happen. We have found a significant correlation between the behavioral changes and the actual calving time of cattle. Hyper-parameter optimization is conducted over the classifiers by using Grid Search approach to determine the optimal value of parameters. The evidence from this study implies that our developed FDNN model outperformed the other four classifiers in terms of accuracy, sensitivity, specificity, and ROC score. This study is the first step towards enhancing our understanding of the impact of RF classifier when it performs together with DNN. We are currently in the process of planning to investigate our model over a bigger benchmark although our results are found promising so far.

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