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Research article

Multilayer perceptron and support vector regression models for feline parturition date prediction

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A R T I C L E I N F O

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A B S T R A C T

A crucial challenge in feline obstetric care is the accurate prediction of the parturition date during late pregnancy. The classic simple linear regression (SLR) model, which employed the fetal biparietal diameter (BPD) as the single input feature, was frequently applied for such prediction with limited accuracy. Since Multilayer Perceptron (MLP) and Support Vector Regression (SVR) are now two of the most potent scientific regression models, this study, for the first time, introduced such models as the new promising tools for feline parturition date prediction. The following features were candidate inputs for our models: biparietal diameter (BPD), litter size, and maternal weight. We observed and compared the performance results for each model. As the best-performed model, MLP delivered the highest coefficient score (0.972 ± 0.006), lowest mean absolute error score (1.110 ± 0.060), and lowest mean squared error score (1.540 ± 0.141), respectively. For the first time in this study, BPD, litter size, and maternal weight were considered the essential features for the innovative MLP and SVR modeling. With the optimized model parameters and the described analytical platform, further verification of these advanced models in feline obstetric practices is feasible.

1. Introduction

Parturition date prediction is a critical issue in feline obstetric care for both owner and practitioner to observe and monitor the queens [1]. In queens with a high risk of dystocia, it is crucial to have a plan for an elective Caesarean section (C-section) close to the anticipated delivery date to ensure the survival and well-being of both mother and newborn [2]. Therefore, the punctual parturition date prediction is considered a critical issue in feline obstetrics. A practical method to determine the date before parturition (DBP) in a pregnant queen is the transabdominal ultrasonographic examination of extrafetal and fetal biometry. From the second half of gestation (4–9 weeks of pregnancy) until the due date, the biparietal diameter (BPD) is the most often used feature to determine DBP [1,3]. Since DBP prediction is more critical in late pregnancy, BPD measurement has become a general practice for feline pregnancy follow-up.

Simple Linear Regression (SLR) is the conventional model for feline DBP prediction, with BPD serving as the only input feature [4]. The model, however, demonstrated a significant accuracy decline as pregnancy advanced. Summary data from previous studies indicated that the confidence intervals of SLR models allowing one-day (±1 day) and two-day (±2 days) errors at the 6th gestation weeks could vary from 53 to 79% and 77–88%. Then they rapidly dropped to 27–51% and 50–70% in the 9th week—the last week of

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gestation [1,3–8]. These studies also utilized various SLR formulas, even the unique one specific to a cat breed [4–6,8,9]. These findings highlight the insufficiency of the model type and input features utilized in the SLR model, presenting a compelling research area to explore more precise models for this particular task. Of note, the advances in data science modeling have provided us with alternative models to deal with such an issue [10,11]. Of note, some cutting-edge regression models, such as Support Vector Regression (SVR), have recently been demonstrated to be more accurate models in dogs, a closely related species to cats [1,3,10].

Multilayer Perceptron (MLP) and Support Vector Regression (SVR) models are among the most popular regression models, well-recognized for their superior performances in scientific and economic research, including those of ecology [12,13], engineering [14–21], and animal fields including feline biomechanic modeling [22–26]. While traditional statistical modeling formulates the relationships between input features and output variables through fixed mathematical equations, MLP can learn from training data using multiple training algorithms and rules. As a result, MLP gains several advantages, including increased capacity. MLP is thus a self-administered model that uses specific learning algorithms to optimize itself as it acquires updated inputs [27]. On the other hand, SVR acknowledges non-linear relationships by processing input data from non-linear to linear space using specific transforming functions—the kernel functions. The kernel function can implement a model in a higher-dimensional space (feature space) without requiring a mapping function from the input space to the feature space. SVR could deal with a non-linear relationship between input

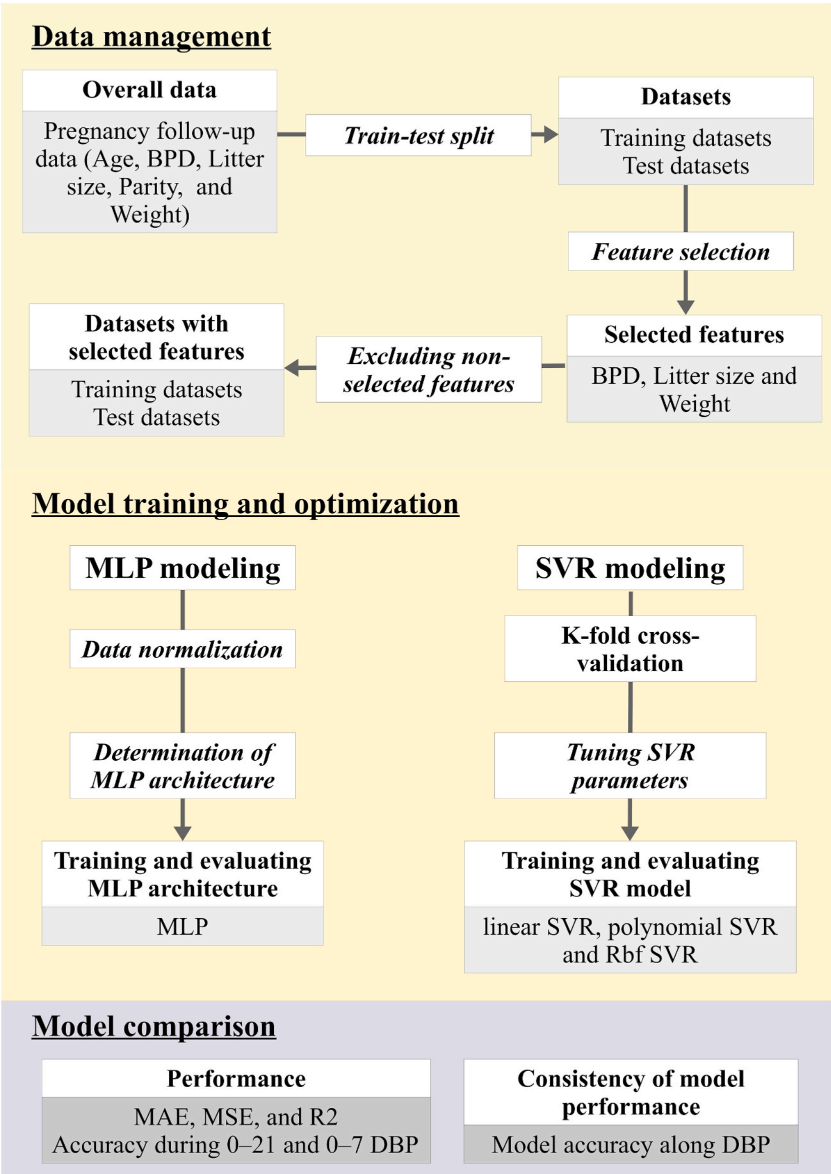

Fig. 1. Methodological workflow. The analysis consisted of 3 major parts, as follows: 1) Data management, 2) Model training and optimization, and 3) Model comparison. The material and methods covered all analytical procedures in detail.

and output since the decision boundary created by a kernel function—the hyperplane—can predict the output value of the SVR model [28]. Due to their robustness in non-linear modeling, MLP and SVR models should be worthy candidates for feline DBP prediction, which SLR fails to explain.

Proper input features are also crucial when constructing new models [29]. In feline-related species like dogs [1,3] and humans [12], there is evidence that several features, besides BPD, can influence the prediction of DBP. In pregnant bitches, maternal weight [10] and litter size [30] could affect DBP prediction. Preterm birth risk in pregnant women increases with advanced maternal age [31] and parity [32]. Since shreds of evidence also supported the possible roles of these parameters on the queen's gestation period [8, 33–35], they should be prospective candidate features in the present feline DBP prediction models.

For the first time, this study introduced MLP and SVR modeling in feline DBP prediction. Concepts and procedures from input feature selection to model optimization were demonstrated in uncomplicated detail. This study also described a methodology for comparing model performances to identify the top-performing model.

2. Materials and methods

2.1. Ethics declarations

This study used anonymously provided secondary data already presented in the database of an animal hospital. This work did not involve the use of animals, and no animals or people are identifiable within this publication.

2.2. Programming environment and python packages

The open-source web application, Jupyter Notebook, was utilized as the platform for Python coding. The research methodology provided a detailed description of each necessary function and its corresponding Python packages.

2.3. Animal data

An animal hospital in Chonburi Province, Thailand, provided the anonymous raw data of pregnant queens presented for routine pregnancy follow-ups from 2015 to 2022. The hospital is certified by the Thailand Animal Hospital Standards and Accreditation—by which all practitioners follow the established internationally recognized high standards ('best practice') of veterinary clinical care for the individual patient. The raw data contained 384 examination results recorded from 128 queens (6–50 months old). The raw data consisted of the queen's age, weight, the ultrasonographic figure of fetal BPD, parity number, and litter size. For each examination, the practitioner always recorded the age and weight of the queen before the ultrasonography. The mean BPD (five repeats for each fetus) of all fetuses presented in the examined queen was calculated and recorded. The litter size (the number of kittens) was determined at least once by radiographic diagnosis. After each parturition, the hospital would confirm the litter size and the parity number of the queen.

2.4. Experimental design

The experiment consisted of three parts: 1) Data management, 2) Model training and optimization, and 3) Model comparison (Fig. 1). In the 'Data management' part, we divided the raw data into the training and test datasets, and then selected only the signified input feature data for the subsequent modeling part. MLP and SVR models were trained and optimized using these prepared datasets in the 'Model training and optimization' part. We then compared the performances of these optimized models in the 'Model comparison' part. We provided all mathematical expressions related to model construction and performance in the supplementary materials and methods.

2.5. Part 1: data management

There were 384 samples of examination results in the raw data. BPD (mm), maternal age (month), maternal weight (kg), parity number, and litter size were the recorded feature data. We divided the raw data into training and testing datasets at a ratio of around 2.73:1 (281 and 103 samples, accordingly) using the 'train_test_split' function of the 'sklearn' package [36]. We provided the testing dataset as the supplementary CSV file. On request, the training dataset could be made available. We implemented the mutual information feature selection method to select features for further modeling using the mutual information feature selection technique by the 'mutual_info_regression' function of the 'sklearn' package [37]. This test gave the importance score for all the feature data—by which this study only considered features with scores higher than 0.1.

2.6. Part 2: model training and optimization

Both MLP and SVR modeling employed the pre-prepared training dataset. Following was the description of the MLP and SVR modeling concepts and procedures.

2.7. MLP modeling

The MLP architecture consists of three types of layers. The input layer is the first layer responsible for inputting feature data for the model. The hidden layer could be either single or multiple. The layer stands between the input and the output layer and is responsible for the model computation. The output layer is the final layer that produces the final output result.

In each layer, the computational units with unique transfer functions—the neurons—are organized with interconnection to comprise the network formation (Fig. 2). Each neuron has an assigned activation function. An activation function is responsible for transforming and computing the neuron input to decide whether that neuron should be activated or not. This process results in a different cumulative output from each neuron for the subsequent output layer. During the MLP training, the process will continuously adjust all neuron weight and bias values with a selected algorithm until optimizing the model performance. For this purpose, the backpropagation technique (BP) is used to obtain model parameters in MLP training by updating weight and bias to lower the output layer's prediction error until optimization. All mathematical expressions associated with the MLP training process in supplementary materials and methods were from previous studies [13,22,23].

2.7.1. Data normalization

Before MLP training, we normalized the training data by the min-max normalization method using the 'preprocessing.MinMaxScaler' function of the 'sklearn' package. The process organized all input values on the same scale between 0 and 1 [38].

2.7.2. Determination of MLP architecture

This study constructed the MLP model based on the sequential architecture—the simple linear stack model. To acquire the model structure, we passed a list of layers (input, hidden, and output layers) to the sequential constructor by the 'keras.Sequential' function of the 'Keras' programming interface [39]. The number of layers and neurons in the MLP architecture was established based on the Principle Component Analysis (PCA) with K-means clustering. Further details about the principle were in Rachmatullah et al., 2021 [40]. Briefly, we calculated PCA using normalized training data. The cumulative principal component (PC) numbers with signified cumulative variances rendered all possible hidden layer numbers of MLP. Each PC would represent each of the hidden layers. For each hidden layer, the optimal K-mean cluster numbers calculated from sample values corresponded to the estimated neuron numbers presented in that layer.

2.7.3. Training and evaluating MLP architecture

This study trained and evaluated all MLP structures from the 'Determination of MLP architecture' process using the programming interface 'Keras' as the framework. We selected the 'Adam' algorithm as the model optimizer. The number of times the algorithm worked through the training dataset (epoch) was 300. The batch size—the sample number used for each training round—was 50. The loss value—the deviation of the predicted value from the real one during the training process—was evaluated by Mean Absolute Error (MAE) and Mean Square Error (MSE). The optimized MLP model was the MLP structure that performed the best, yielding the lowest MAE and MSE scores. We provided a detailed description of the optimized MLP architecture in the supplementary information.

2.8. SVR modeling

In several fields of scientific research, SVR is considered an alternative model to MLP [41–45]. The concept behind SVR was to

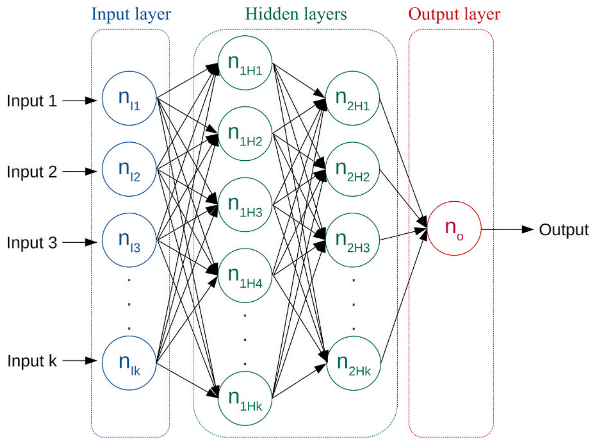

Fig. 2. MLP architecture. An example provided the model with two hidden layers. Each model layer contained a varied number of neurons (n). The neurons in the input layer (n_I) were responsible for k numbers of input feature values (n_{I1} to n_{Ik}), with only one output from the output neuron (n_O) in the output layer. The neurons in hidden layers (n_{1H} and n_{2H}) computed their results using the equipped functions with the assigned weight values. The organized connections among these neurons formed a unique MLP structure.

obtain the best-fit plane, known as a hyperplane, to cover the maximum number of data points in the data space. Such a hyperplane represented the SVR model. The raw input data requires transformation to achieve this higher-dimensional space for modeling. This task could make use of various Kernel functions. Given that the optimized hyperplane produced by a model was reasonably close to the actual values, it was possible to predict the output (DBP for this study) given the known input features [28].

2.8.1. K-fold cross-validation

Using the 'cross_validated' function from the 'optunity' package, we performed the 5-fold cross-validation on the training dataset [46]. In brief, the original training dataset would generate five new random training datasets of equal size (5 iterations). The process divided each new training dataset into five partitions for each training round. The model training process used four of them, while the leftover was for evaluating the performance of the generated model. The process would repeat with all partitions to tune for the best SVR parameters.

2.8.2. Tuning SVR parameters

We used the new training dataset generated from 5-fold cross-validation for tuning SVR parameters. Base on their accuracies in predicting canine DBP [10], this study also employed three kernel functions—linear, polynomial, and radial basis function (Rbf)—for input data transformation. This process created three SVR models—linear SVR, polynomial SVR, and Rbf SVR models—and each required parameter tuning. For the tuning procedure outlined in our prior work, we used Bayesian optimization provided by the 'Opportunity' package [10]. All mathematical expressions of all kernel functions in supplementary materials and methods were from previous studies [47].

2.8.3. Training and evaluating SVR model

After tuning parameters, we evaluated the performances of the optimized SVR models with different kernel functions—linear SVR, polynomial SVR, and Rbf SVR using module functions of the 'scikit-learn' package.

2.9. Part 3: model comparisons

2.9.1. Performance comparison

This study evaluated the performance of all models using an identical approach. Apart from the coefficient of determination (R2), mean absolute error (MAE), and mean squared error (MSE), we also calculated the model accuracy during the 6th (0–21 DBP) and last week (0–7 DBP) of gestation, similar to those performed in most previous SLR studies.

2.9.2. R2, MAE, and MSE scores

We utilized R2, MAE, and MSE to compare the performance among the MLP and SVR models [10]. We utilized the 'sklearn.metrics' module of the 'scikit-learn' package to calculate the performance scores for these statistics. We performed bootstrap re-sampling on the testing dataset (1000 times) to acquire the standard deviation (SD) value of each score for every model. This process allowed score comparison among all models (one-way ANOVA with post hoc Tukey HSD).

2.9.3. Accuracy during 0–21 and 0–7 DBP

We calculated the model accuracies in percentages, allowing one-day (±1 day) and two-day (±2 days) errors, focusing on the 6th and last gestation weeks (0–21 and 0–7 DBP, respectively). With the additional step of bootstrap re-sampling on the testing dataset (1000 times), this study reported the mean accuracy value along with its SD.

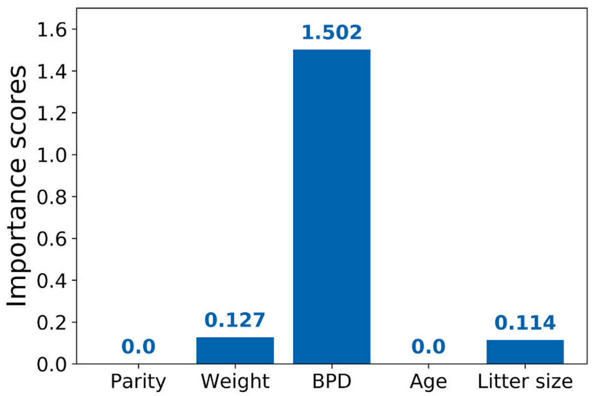

Fig. 3. Feature selection plot. The plot displayed the importance scores of all feature data acquired from Mutual information feature selection.

2.10. Consistency of model performance

We calculated the discrepancies between predicted and actual DBP (actual DBP - predicted DBP) from 0 to 33 DBP. To examine how consistently each model performed at various DBP, we computed and plotted the mean and 95% confidence interval of these discrepant values for all models. This plot allowed notification of each model performance at the particular DBP of interest.

2.11. Data availability

The training dataset used in this study will be from the corresponding author upon request. The test dataset was provided as the supplementary CSV file.

3. Results

3.1. Important features for modeling

The features presented in the raw data were as follows: BPD, maternal age, maternal weight, parity number, and litter size. Mutual information feature selection identified three features—BPD, litter size, and maternal weight—with importance scores higher than 0.1 (Fig. 3). According to the results, BPD rendered the highest score (1.502) when compared to the other features.

3.2. Optimized MLP architecture and SVR parameters

Since only BPD, litter size, and maternal weight were the selected features, the data of these normalized features were the inputs of all models. The construction of various MLP architectures was archived based on the Principle Component Analysis (PCA) with K-means clustering analyses as described in the material and methods. With the training dataset, we obtained nine principal components (PCs). More than 90% of the total variance was described by the first PC implying that the candidate MLP structure contained only one hidden layer.

The K-means clustering of the first PC resulted in 46 clusters, representing the number of candidate neurons. We further fine-tuned the neuron numbers by training seven MLP models with neuron numbers ranging from 43 to 49 and comparing their performances (Table 1). The best-performing model contained 48 neurons, resulting in the best coefficient of determination (R2), mean absolute error (MAE), and mean squared error (MSE) scores. We illustrated the finalized MLP structure with a detailed description (Fig. 4).

All parameters of the linear SVR, polynomial SVR and Rbf SVR models were tuned as described in the material and methods. For more details, we provided information on the ranges of values used for tuning all SVR parameters and the optimized parameter values used in the finalized SVR models in the supplementary tables (Supplementary Tables 1 and 2).

3.3. Performance comparison among MLP and SVR models

R2, MAE, and MSE scores acquired among all optimized models were computed and compared (Tables 2 and 3). The Rbf SVR model performed the worst out of all the models. The MLP model could outperform all other models in terms of MAE and MSE scores ($P \leq 0.01$).

The model accuracy in percentages allowing one-day (±1 day) and two-day (±2 days) errors on the 6th (0–21 DBP) and the last (0–7 DBP) gestation week were computed and compared (Table 4). While there were minor differences in accuracy results among models, the mean accuracy of all models except the Rbf SVR on the last gestation week was greater than 53% and 82% for 1-day and 2-day errors, respectively.

To see how consistently each model could perform at various DBP, we displayed the error days mispredicted in each DBP by 95% confidence interval areas. All models showed similar accuracy trends from 0 to 33 DBP (color lines in Fig. 5). Of note, the 95% confidence interval areas of most models were within two-day errors (±2 days) (color-shaded areas in Fig. 5), except for the Rbf SVR model (the blue-shaded areas in Fig. 5).

Table 1
Performances of trained MLP models with different neuron numbers in the hidden layer.

Neuron numbers	[a]R2 score	[b]MAE score	[c]MSE score
43 neurons	0.921	2.103	6.607
44 neurons	0.919	2.123	6.792
45 neurons	0.924	2.065	6.344
46 neurons	0.920	2.112	6.705
47 neurons	0.922	2.094	6.543
48 neurons	0.925	2.061	6.298
49 neurons	0.919	2.121	6.802

[a] R2 - Coefficient of determination.
[b] MAE - Mean absolute error.
[c] MSE - Mean squared error.

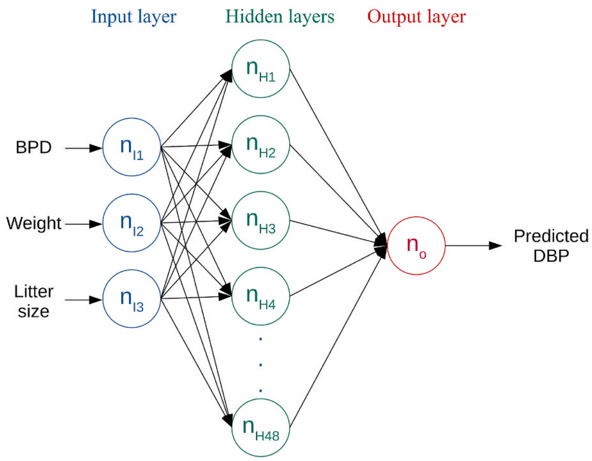

Fig. 4. Optimized MLP model structure. The input layer of the optimized MLP model consisted of 3 neurons for BPD, litter size, and weight input values. The hidden layer had 48 neurons with Exponential linear unit (Elu) as their activation functions. The output layer of the model had a single neuron with the linear function for calculating the predicted DBP.

Table 2
R2, MAE and MSE scores.

Model	[a]R2 score			[b]MAE score			[c]MSE score		
MLP	0.972	±	0.006	1.110	±	0.060	1.540	±	0.141
Linear SVR	0.971	±	0.007	1.117	±	0.065	1.581	±	0.168
Polynomial SVR	0.968	±	0.008	1.129	±	0.067	1.641	±	0.170
Rbf SVR	0.950	±	0.017	1.168	±	0.098	2.063	±	0.310

[a] R2 - Coefficient of determination.
[b] MAE - Mean absolute error.
[c] MSE - Mean squared error.

Table 3
Posthoc Tukey HSD results.

Compared models		P-value		
Model 1	*Model 2*	*[a]R2*	*[b]MAE*	*[c]MSE*
MLP	Linear SVR	0.900	0.165	0.007
MLP	Polynomial SVR	0.340	0.001	0.379
MLP	Rbf SVR	0.001	0.001	0.001
Linear SVR	Polynomial SVR	0.774	0.002	0.001
Linear SVR	Rbf SVR	0.001	0.001	0.001
Polynomial SVR	Rbf SVR	0.001	0.001	0.001

[a] R2 - Coefficient of determination.
[b] MAE - Mean absolute error.
[c] MSE - Mean squared error.

Table 4
Model accuracy during 0–21 and 0–7 DBP.

Model	*[a]0–21 DBP (Mean* ± SD)						*[b]0–7 DBP (Mean* ± SD)					
	±1 day error			±2 day error			±1 day error			±2 day error		
MLP	49.653	±	8.072	83.929	±	6.074	53.478	±	6.540	85.152	±	5.030
Linear SVR	54.745	±	8.234	85.279	±	5.597	53.935	±	7.686	85.543	±	5.265
Polynomial SVR	55.376	±	8.088	81.132	±	6.278	56.043	±	8.143	82.130	±	5.669
Rbf SVR	58.824	±	7.995	73.845	±	7.055	60.283	±	7.179	76.348	±	5.607

[a] 0-21 DBP – Comparable to the 6th gestation week.
[b] 0-7 DBP – Comparable to the last gestation week.

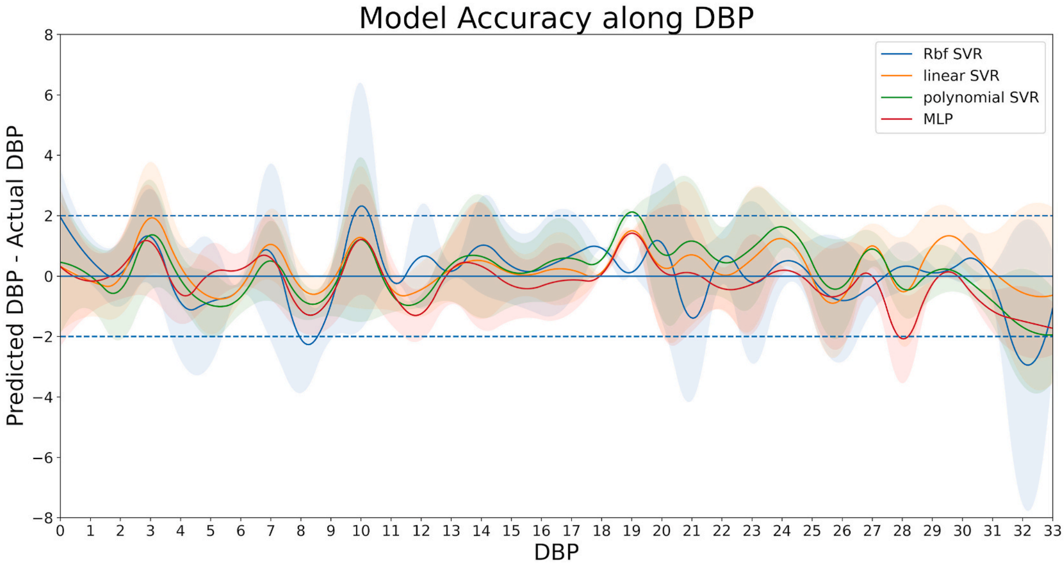

Fig. 5. The plot of the discrepancy between predicted and real DBP. This plot showed the mean differences between predicted and real DBP (real DBP – predicted DBP) from day 0 to day 33 of all models. The graph displayed the values of the 95% confidence intervals in hues that matched the colors of the model. The zero line indicated the precise prediction. The Rbf SVR, Linear SVR, Polynomial SVR, and MLP models were blue, orange, green, and red, as described in the legend. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

4. Discussion

The prediction of parturition dates presents a significant challenge in the clinical management of pregnant felines. Accurate DBP prediction enables owners and veterinarians to plan better for delivery assistance, reducing the risks faced by newborns during the peripartum period. Previous studies introduced the simple linear regression (SLR) model for such a task. However, SLR still shows limited accuracy in this regard, along with the lack of consideration of other crucial features, such as maternal weight or size, that likely influence the accuracy of this model.

Feline obstetrics practitioners and researchers have long relied on SLR model for predicting parturition dates. For the first time, this study introduced kernel-based machine learning model—SVR and deep learning model—MLP to this field. Supported by previous success in canine DBP predictions [10], SVR model also shares a conceptual affinity with feline DBP predictions. On the other hand, MLP model, characterized by its uncomplicated structure and versatile applicability, proves well-suited for introducing deep learning models to veterinary practitioners/researchers who are commonly unfamiliar with modeling. This study used a considerable training sample size with a separate test dataset, in contrast to earlier reported SLR models. The reported models, particularly the MLP, produced low variation between the predicted and actual DBP, as evidenced by low MAE and MSE scores. Even during the last week, the mean accuracy of all models ranged from 76.348% to 85.543% ($\pm$2 day error). The results thus suggested that MLP model excelled other models in managing arbitrary non-linear relationships among feline features—BPD, litter size, and maternal weight—enabling accurate DBP prediction utilizing the model layers and activation functions.

In practice, the radiography of the fetal skull at 38 days of pregnancy or later was a requirement for the litter size confirmation [48], which was a significant limitation for all introduced models. The unstable 95% confidence interval areas of all models in the consistency plot (Fig. 5) also suggested further model training with larger datasets to improve such performance. For those aspiring to generate more models based on the provided methodology, we recommended a larger sample size to enhance the training process. This issue was critical, particularly for MLP modeling, for which a large sample size was preferable [27,49]. Despite the preferable accuracy, comprehending the internal logic behind MLP and SVR proved challenging due to their complex nature, thereby restricting model interpretation and understanding of their prediction processes.

The process of feature selection is crucial to effective modeling. The lack of relevant input features could severely mislead the training process resulting in a poor-performed model. For the traditional SLR model, BPD was the only input feature [1,3]. This previous notification suggested BPD as the critical feature for DBP prediction modeling. With the highest importance score, our analysis also supported BPD as the most crucial feature for DBP prediction. Besides from BPD, the test also identified litter size and maternal weight as the essential features for feline DBP prediction (Fig. 3). Concordant with the evidence in dogs [1,10,30], our results indicated litter size and maternal weight as the secondary factors affecting feline parturition date prediction. This notice further supported the similar nature of pregnancy in dogs and cats.

There are several approaches to architect an MLP structure [40,50]. Since this could result in a different MLP topology, we only claimed the optimized MLP structure in this study based on our modified method. This note also applied to all optimized SVR models. According to the results, the Rbf SVR model showed the worst performance in terms of R2, MAE, and MSE scores. The MLP model, on the other hand, was determined to be the most accurate model (highest R2, lowest MAE, and lowest MSE scores).

The MAE score represented the average difference between the predicted DBP and the actual one (day). The MSE score, on the other hand, evaluated a similar difference with a rigid enhancement due to its squaring operation. In terms of application, these scores would provide better insight into day ranges with potential parturition—the critical information for both the owner and practitioner to observe the mother. For instance, the 1.110 ± 0.060 MAE score of the MLP model implied that the average error of DBP predicted by the MLP model was within 1.110 ± 0.060 days from the predicted parturition date. When applying the model, one should anticipate the queen giving birth inside this time window.

The majority of earlier research measured the SLR model's performance using the percentage accuracy with a one- or two-day error. These studies usually mention the concern about the rapidly declining performance of SLR from the 6th to the last week of gestation (78–88% to 50–70% for two-day error) [1,3–8]. On the contrary, MLP and SVR models in this study manifested comparable high accuracy during the 6th to the final week of gestation (Table 4). Unlike the well-recognized SLR, these novel models still require long-term verification with larger test datasets in the future.

MLP and all SVR models rendered R2 scores higher than 0.95 (Table 2). In other words, these models could explain more than 95% of the DBP's variability in the data. Even though the R2 scores indicated how well a model could handle the predicted result's variation, their performances along 0–33 DBP were not entirely consistent, especially for the Rbf SVR. In support of this notice, the Rbf SVR also gave the highest MSE score, reflecting the remarkable variations during the prediction of some DBP. Since the ideal model should render highly consistent and accurate results, more model training with larger datasets in future studies was encouraged to enhance all model performances, even for the best-performing MLP model.

5. Conclusion

In conclusion, this study successfully established the novel MLP and SVR modeling methodologies for predicting feline DBP. In addition to BPD, we identified litter size and maternal weight as the essential factors influencing DBP prediction. We remarked on MLP as the best-performing model, while the Rbf SVR model was the worst. The current study provided ready-to-use model structures and all tuned parameters. Further validation of these models with pregnancy-follow-up data was encouraged for researchers in the feline obstetric field. To improve future feline DBP prediction, we also encouraged the establishment of other well-validated data science models in addition to SLR.

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Data availability statement

Data included in article/supp. material/referenced in article.

CRediT authorship contribution statement

Thanida Sananmuang: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Supervision, Writing – original draft, Writing – review & editing. **Kanchanarat Mankong:** Data curation, Investigation, Methodology, Resources. **Kaj Chokeshaiusaha:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing.

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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Appendix A. Supplementary data

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References

[1] M. Beccaglia, S. Alonge, C. Trovo', G.C. Luvoni, Determination of gestational time and prediction of parturition in dogs and cats: an update, Reprod. Domest. Anim. 51 (2016) 12–17, https://doi.org/10.1111/rda.12782.

[2] E. Michel, M. Spörri, S. Ohlerth, I. Reichler, Prediction of parturition date in the bitch and queen, Reprod. Domest. Anim. 46 (2011) 926–932, https://doi.org/10.1111/j.1439-0531.2011.01763.x.

[3] M. Beccaglia, G.C. Luvoni, Prediction of parturition in dogs and cats: accuracy at different gestational ages, Reprod. Domest. Anim. 47 (2012) 194–196, https://doi.org/10.1111/rda.12006.

[4] M. Beccaglia, P. Anastasi, E. Grimaldi, A. Rota, M. Faustini, G.C. Luvoni, Accuracy of the prediction of parturition date through ultrasonographic measurement of fetal parameters in the queen, in: Veterinary Research Communications, Vet Res Commun, 2008, https://doi.org/10.1007/s11259-008-9107-1.

[5] E. Topie, D. Bencharif, L. Briand, D. Tainturier, Monitoring the foetal phase of gestation in the queen with a 12.5-MHz ultrasound probe and prediction of the parturition by combining the measurements of head and abdominal diameters, Reprod. Domest. Anim. 50 (2015) 560–566, https://doi.org/10.1111/rda.12523.

[6] R. Keiser, I. Reichler, O. Balogh, Are foetal ultrasonographic and maternal blood progesterone measurements near parturition reliable predictors of the time of birth in the domestic cat? Reprod. Domest. Anim. 52 (2017) 487–494, https://doi.org/10.1111/rda.12939.

[7] M.C. García Mitacek, M.C. Stornelli, R.G. Praderio, R.L. de la Sota, M.A. Stornelli, Ultrasonographic and progesterone changes during Days 21 to 63 of pregnancy in queens, Theriogenology 84 (2015) 1131–1141, https://doi.org/10.1016/j.theriogenology.2015.06.014.

[8] L. Gatel, D. Rault, K. Chalvet-Monfray, J. Saunders, S. Buff, Prediction of parturition time in queens using radiography and ultrasonography, Anat. Histol. Embryol. 44 (2015) 241–246, https://doi.org/10.1111/ahe.12130.

[9] P. Socha, T. Janowski, Development of specific fetometric formulas of ICC and BP for predicting the parturition date in Maine Coon queens, Reprod. Domest. Anim. 54 (2019) 622–626, https://doi.org/10.1111/rda.13404.

[10] T. Sananmuang, K. Mankong, S. Ponglowhapan, K. Chokeshaiusaha, Support vector regression algorithm modeling to predict the parturition date of small - to medium-sized dogs using maternal weight and fetal biparietal diameter, Vet. World 14 (2021) 829–834, https://doi.org/10.14202/vetworld.2021.829-834.

[11] D. Xu, Y. Song, Y. Meng, B. István, Y. Gu, Relationship between firefighter physical fitness and special ability performance: predictive research based on machine learning algorithms, Int. J. Environ. Res. Publ. Health 17 (2020) 7689, https://doi.org/10.3390/ijerph17207689.

[12] A. Jahani, M. Saffariha, Modeling of trees failure under windstorm in harvested Hyrcanian forests using machine learning techniques, Sci. Rep. 11 (2021) 1124, https://doi.org/10.1038/s41598-020-80426-7.

[13] M. Saffariha, A. Jahani, R. Jahani, S. Latif, Prediction of hypericin content in Hypericum perforatum L. in different ecological habitat using artificial neural networks, Plant Methods 17 (2021) 10, https://doi.org/10.1186/s13007-021-00710-z.

[14] N. Parveen, S. Zaidi, M. Danish, Artificial intelligence (AI)-based friction factor models for large piping networks, Chem. Eng. Commun. 207 (2020) 213–230, https://doi.org/10.1080/00986445.2019.1578757.

[15] N. Parveen, S. Zaidi, M. Danish, Development and analysis of data-driven models for predicting the bed depth profile of solids flowing in a rotary kiln, Adv. Powder Technol. 31 (2019), https://doi.org/10.1016/j.apt.2019.11.023.

[16] N. Parveen, S. Zaidi, M. Danish, Comparative analysis for the prediction of boiling heat transfer coefficient of R134a in micro/mini channels using artificial intelligence (AI)-based techniques, Int. J. Model. Simulat. 40 (2020) 114–129, https://doi.org/10.1080/02286203.2018.1564809.

[17] N. Parveen, S. Zaidi, M. Danish, Support vector regression: a novel soft computing technique for predicting the removal of cadmium from wastewater, Indian J. Chem. Technol. 27 (2020) 43–50.

[18] N. Parveen, S. Zaidi, M. Danish, Support vector regression (SVR)-based adsorption model for Ni (II) ions removal, Groundwater for Sustainable Development 9 (2019) 100232, https://doi.org/10.1016/j.gsd.2019.100232.

[19] N. Parveen, S. Zaidi, M. Danish, Modeling of flow boiling heat transfer coefficient of R11 in mini-channels using support vector machines and its comparative analysis with the existing correlations, Heat Mass Tran. 55 (2019) 151–164, https://doi.org/10.1007/s00231-018-2459-3.

[20] N. Parveen, S. Zaidi, M. Danish, Development of SVR-based model and comparative analysis with MLR and ANN models for predicting the sorption capacity of Cr(VI), Process Saf. Environ. Protect. 107 (2017) 428–437, https://doi.org/10.1016/j.psep.2017.03.007.

[21] N. Parveen, S. Zaidi, M. Danish, Support vector regression prediction and analysis of the copper (II) biosorption efficiency, Indian Chem. Eng. 59 (2017) 295–311, https://doi.org/10.1080/00194506.2016.1270778.

[22] E. Arulmozhi, J.K. Basak, T. Sihalath, J. Park, H.T. Kim, B.E. Moon, Machine learning-based microclimate model for indoor air temperature and relative humidity prediction in a swine building, Animals 11 (2021) 222, https://doi.org/10.3390/ani11010222.

[23] X. Chen, H. Zheng, H. Wang, T. Yan, Can machine learning algorithms perform better than multiple linear regression in predicting nitrogen excretion from lactating dairy cows, Sci. Rep. 12 (2022) 12478, https://doi.org/10.1038/s41598-022-16490-y.

[24] D. Xu, H. Zhou, Q. Zhang, J.S. Baker, U.C. Ugbolue, Z. Radak, X. Ma, F. Gusztav, M. Wang, Y. Gu, A new method proposed to explore the feline's paw bones of contributing most to landing pattern recognition when landed under different constraints, Front. Vet. Sci. 9 (2022). https://www.frontiersin.org/articles/10.3389/fvets.2022.1011357. (Accessed 16 June 2023).

[25] D. Xu, H. Zhou, X. Jiang, S. Li, Q. Zhang, J.S. Baker, Y. Gu, New insights for the design of bionic robots: adaptive motion adjustment strategies during feline landings, Front. Vet. Sci. 9 (2022). https://www.frontiersin.org/articles/10.3389/fvets.2022.836043. (Accessed 16 June 2023).

[26] D. Xu, W. Quan, H. Zhou, D. Sun, J.S. Baker, Y. Gu, Explaining the differences of gait patterns between high and low-mileage runners with machine learning, Sci. Rep. 12 (2022) 2981, https://doi.org/10.1038/s41598-022-07054-1.

[27] O.I. Abiodun, A. Jantan, A.E. Omolara, K.V. Dada, A.M. Umar, O.U. Linus, H. Arshad, A.A. Kazaure, U. Gana, M.U. Kiru, Comprehensive review of artificial neural network applications to pattern recognition, IEEE Access 7 (2019) 158820–158846, https://doi.org/10.1109/ACCESS.2019.2945545.

[28] F. Zhang, L.J. O'Donnell, Support Vector Regression, Machine Learning, 2020, pp. 123–140, https://doi.org/10.1016/b978-0-12-815739-8.00007-9.

[29] L.D.D. Desboulets, A review on variable selection in regression analysis, Econometrics 6 (2018), https://doi.org/10.3390/econometrics6040045.

[30] B.E. Eilts, A.P. Davidson, G. Hosgood, D.L. Paccamonti, D.G. Baker, Factors affecting gestation duration in the bitch, Theriogenology 64 (2005) 242–251, https://doi.org/10.1016/j.theriogenology.2004.11.007.

[31] I. Glick, E. Kadish, M. Rottenstreich, Management of pregnancy in women of advanced maternal age: improving outcomes for mother and baby, Int. J. Wom. Health 13 (2021) 751–759, https://doi.org/10.2147/IJWH.S283216.

[32] B. Koullali, M.D. Van Zijl, B.M. Kazemier, M.A. Oudijk, B.W.J. Mol, E. Pajkrt, A.C.J. Ravelli, The association between parity and spontaneous preterm birth: a population based study, BMC Pregnancy Childbirth 20 (2020) 1–8, https://doi.org/10.1186/s12884-020-02940-w.

[33] J. Musters, J. de Gier, H.S. Kooistra, A.C. Okkens, Questionnaire-based survey of parturition in the queen, Theriogenology 75 (2011) 1596–1601, https://doi.org/10.1016/j.theriogenology.2010.12.020.

[34] L. Gatel, E. Rosset, K. Chalvet-Monfray, S. Buff, D.N. Rault, Relationships between fetal biometry, maternal factors and birth weight of purebred domestic cat kittens, Theriogenology 76 (2011) 1716–1722, https://doi.org/10.1016/j.theriogenology.2011.07.003.

[35] A.H. Sparkes, K. Rogers, W.E. Henley, D.A. Gunn-Moore, J.M. May, T.J. Gruffydd-Jones, C. Bessant, A questionnaire-based study of gestation, parturition and neonatal mortality in pedigree breeding cats in the UK, J. Feline Med. Surg. 8 (2006) 145–157, https://doi.org/10.1016/j.jfms.2005.10.003.

[36] P. Pedregosa, F, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, Blondel, A. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, E. Passos, D. Cournapeau, M. Brucher, M. Perrot, F. Duchesnay, G. Pedregosa, A. Varoquaux, V. Gramfort, B. Michel, O. Thirion, M. Grisel, P. Blondel, R. Prettenhofer, V. Weiss, J. Dubourg, A. Vanderplas, D. Passos, M. Cournapeau, M. Brucher, É. Perrot, Duchesnay, Scikit-learn: machine learning in Python, J. Mach. Learn. Res. 12 (2011) 2825–2830.

[37] B.C. Ross, Mutual information between discrete and continuous data sets, PLoS One 9 (2014), https://doi.org/10.1371/journal.pone.0087357.

[38] A. Kumar Dharamvir, Data normalization techniques on intrusion detection for dataset applications, International Journal of Advanced Science and Technology 29 (2020) 5083–5093.

[39] A. Gulli, Title Page Deep Learning with Keras Implement neural networks with Keras on Theano and TensorFlow, n.d. https://books.google.com/books/about/Deep_Learning_with_Keras.html?hl=th&id=20EwDwAAQBAJ (accessed May 4, 2022)..

[40] M.I.C. Rachmatullah, J. Santoso, K. Surendro, Determining the number of hidden layer and hidden neuron of neural network for wind speed prediction, PeerJ Computer Science 7 (2021) 1–19, https://doi.org/10.7717/PEERJ-CS.724.

[41] B. Chamnanthongpaivanh, J. Chatchawalsaisin, O. Kittithreerapronchai, Artificial neural network and support vector regression modeling for prediction of mixing time in wet granulation, Journal of Pharmaceutical Innovation (2021), https://doi.org/10.1007/s12247-021-09597-8.

[42] M. Borji, A. Malekian, A. Salajegheh, M. Ghadimi, Multi-time-scale analysis of hydrological drought forecasting using support vector regression (SVR) and artificial neural networks (ANN), Arabian J. Geosci. 9 (2016), https://doi.org/10.1007/s12517-016-2750-x.

[43] H. Ahmadi, M. Rodehutscord, Application of artificial neural network and support vector machines in predicting metabolizable energy in compound feeds for pigs, Front. Nutr. 4 (2017), https://doi.org/10.3389/fnut.2017.00027.

[44] A. Kipkosgei Lagat, Support vector regression and artificial neural network approaches: case of economic growth in East Africa community, Am. J. Theor. Appl. Stat. 7 (2018) 67, https://doi.org/10.11648/j.ajtas.20180702.13.

[45] M. Abdel-Sattar, A.M. Aboukarima, B.M. Alnahdi, Application of artificial neural network and support vector regression in predicting mass of ber fruits (Ziziphus mauritiana Lamk.) based on fruit axial dimensions, PLoS One 16 (2021), https://doi.org/10.1371/journal.pone.0245228.

[46] M. Claesen, J. Simm, D. Popovic, B.L.R. De Moor, Hyperparameter Tuning in Python Using Optunity, TCMM, 2014, pp. 6–7.

[47] S. Rüping, SVM Kernels for Time Series Analysis, 2001. Technical Reports, https://ideas.repec.org/p/zbw/sfb475/200143.html. (Accessed 24 November 2022).

[48] D.R. Haney, J.K. Levy, S.M. Newell, J.P. Graham, S.P. Gorman, Use of fetal skeletal mineralization for prediction of parturition date in cats, J. Am. Vet. Med. Assoc. 223 (2003) 1614–1616, https://doi.org/10.2460/javma.2003.223.1614.

[49] A. Vabalas, E. Gowen, E. Poliakoff, A.J. Casson, Machine learning algorithm validation with a limited sample size, PLoS One 14 (2019) e0224365, https://doi.org/10.1371/journal.pone.0224365.

[50] S. Lee, J. Ha, M. Zokhirova, H. Moon, J. Lee, Background information of deep learning for structural engineering, Arch. Comput. Methods Eng. 25 (2018) 121–129, https://doi.org/10.1007/s11831-017-9237-0.