FEATURE EXTRACTION AND SVM ANALYSIS FOR ACCURATE IDENTIFICATION OF INDIVIDUAL SIKA DEER: A DEEP LEARNING APPROACH

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Abstract

Accurate identification of individual wildlife is essential for effective species management and conservation. However, it becomes particularly challenging when unique features, like spot shapes and sizes, serve as the sole distinguishing characteristics, as in the case with Sika deer. This research aims to enhance the process of identifying individual Sika deer by employing a series of deep learning pipelines encompassing object detection, tracking, and automatic segmentation techniques facilitated by segment anything modules based on object detection. Through automatic segmentation contours are generated and various features including color channels, textures, and geometric attributes of the masked Sika deer, were extracted. Subsequently, Support Vector Machine (SVM) analysis was conducted to establish decision boundaries for individual Sika deer identification. We analyzed 2799 image datasets containing images of seven individual Sika deer captured by three camera traps deployed in farmland of Hokkaido, Japan over a span of 60 days. During our analysis, we observed multicollinearity (VIF > 10) within the datasets. To address this, Principal Component Analysis (PCA) was conducted on the extracted features, wherein PCA1 and PCA2, which collectively accounted for over 80% of the variance, were selected for subsequent Support Vector Machine (SVM) analysis. Utilizing the Radial Basis Function (RBF) kernel, which yielded a cross-validation score of 0.97, proved to be the most suitable choice for our research. Hyperparameter optimization, facilitated by the GridSearchCV library, determined the gamma value of 10 and C value as 100. The OneVsRest SVM classifier achieved an impressive overall accuracy of 0.99 for both training and testing datasets of Sika deer images. This study introduces a precise model for identifying individual Sika deer using video frame, aiding conservationists and researchers in effectively monitoring and protecting this species.

Keywords: *Identification, Sika deer, Support Vector Machine, Principal Component Analysis, Kernel*

1. INTRODUCTION

Accurate identification of individual wildlife is paramount for the success of conservation efforts [1]. Various methods, such as mark-capture recapture, radiotelemetry, and GPS tracking [2]-[3], have been employed for this purpose. However, these techniques often necessitate capturing the target species and can result in negative impacts associated with tag attachment.

In recent years, computer vision technology has emerged as the most efficient method for automatically monitoring individual species using extensive image and video datasets obtained from wildlife camera traps. This sophisticated approach involves automatically extracting features from the target species captured by camera traps and is advancing rapidly with copious data and improved computational strength such as Graphics Processing Units (GPUs). Different Convolutional Neural Network (CNN) architectures have been explicitly used for classification and feature extraction tasks on wildlife [4]-[5]. However, advanced classification architectures often require enormous image datasets and can be particularly challenging when unique features such as spot shapes and sizes serve as the sole distinguishing characteristics, as is the case with Sika deer. This study presents a method for analyzing Sika deer features, such as color channels, textures, and various geometric attributes like area, perimeters, and eccentricity of the masked Sika deer. The results demonstrate that this method efficiently identifies individual Sika deer.

This research was conducted in Hokkaido, Japan, where the population of Sika deer was expected to have expanded by 70% over the last three decades [6]. This expansion has increased the carrying capacity while causing forest fragmentation into small patches [7] and has been detrimental to agricultural crops and forestry plantations [8]. The overpopulation of Sika deer is primarily attributed to the absence of predators such as wolves *Canis lupus*, leading to difficulties in managing the population [7].

Due to the uncontrolled overpopulation of Sika deer and its damaging effects causing economic losses, urgent and proper management is essential. Individual identification of each Sika deer is a crucial step in this process. While individual identification of wildlife has been widely conducted in different species such as zebras, and salamanders, there is a dearth of understanding regarding Sika deer, despite the urgent need for their management. The primary goal of this research was to individually identify Sika deer based on different extracted features through deep learning pipelines.

2. MATERIALS AND METHODS

Initially, we adopted the Yolov8 architecture to create an object detection module specifically performed for recognizing a single class: "Sika deer". This module aimed to accurately detect the target species. We employed video data in our research and utilized the DeepSort tracker module to track the movement of each sika deer, assigning a unique ID to each detection. Following this, we integrated the "segment-anything" architecture to automatically segment and localize sika deer within the bounding boxes generated by the object detection with tracker module. Segmentation was crucial for extracting distinct features from each sika deer. These features were then passed through Support Vector Machine (SVM) to establish decision boundaries for each identified instance of a sika deer (Fig. 1).

2.1. Dataset

We installed three camera traps in farmland, positioned at a height of 100 m from the base of a tree, specifically chosen for capturing images of Sika deer [9]. Over a 60-days period (June 1, 2023 – August 3, 2023), we gathered 25 videos featuring the presence of Sika deer. Our dataset included seven individual Sika deer (Fig. 2). To mitigate bias, we used Sika deer video of different environmental conditions of both day and night along with Sika deer near and far from the camera trap deployment center for all individuals.

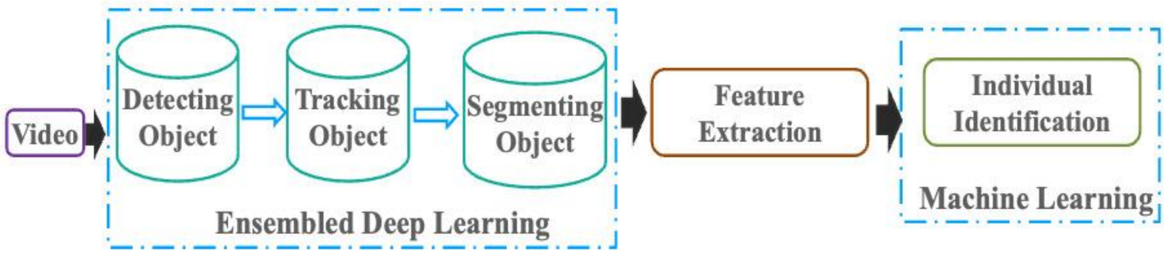


Fig. 1. Overall pipeline for individual sika deer identification.

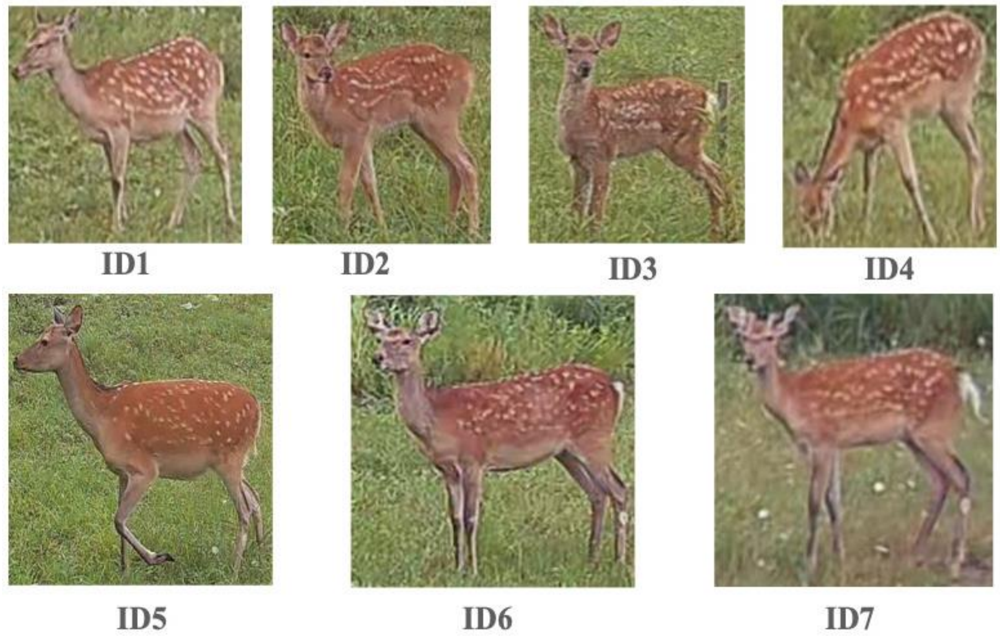


Fig. 2. Sika deer individuals observed at our deployed camera traps.

2.2. Ensembled Deep Learning Architecture

2.2.1. Object Detection Module

We converted the videos into frames to employ them in training within an object detection framework. Specifically, we utilized 2861 frames for the purpose of identifying sika deer. We used CSDPDarknet53 as its backbone consisting of 53 convolutional layers available in different sizes (Fig. 3). Our chosen framework was Yolov8n, where "n" signifies the Nano version known for its compactness and speed. The training regimen involved a batch size of 1 and image set to a resolution of 3840 (same as original video frame resolution), spanning 200 epochs. Singularly, Sika deer constituted the sole class within the dataset, which was labeled in Pascal VOC format, denoting bounding boxes in pixel coordinates.

Initially, we converted this label to YOLO format, representing bounding boxes in normalized "xywh" coordinates (ranging from 0 and 1), where "x" and "y" represented the centroid coordinates of the bounding box, while "w" and "y" represented the width and height, respectively. Prior to training, we performed data augmentation techniques such as flipping, cropping, and rotation to enhance dataset diversity, thus enhancing model performance. We tested our trained model on the video captured by the camera traps.

2.2.2. Tracker Module

We implemented object detection to facilitate tracking in our research. Specifically, we integrated the DeepSort tracker with object detection to assign unique IDs to individual sika deer featured in the video footage. Our videos typically consist of multiple Sika deer within each frame (Fig. 4). DeepSort combines motion and appearance descriptors to track Sika deer based on their velocity, motion patterns, and appearance features [10]. In this context, DeepSort served as a re-identification framework, enabling the continuous tracking of Sika deer across all frames of the video, utilizing cosine distance as the metric for tracking. We set the "max_age" parameter, which determines the maximum number of frames a track can be inactive before removal from the tracker, to 45. Additionally, we applied a confidence threshold of 0.8 for effective tracking purposes (Fig. 4).

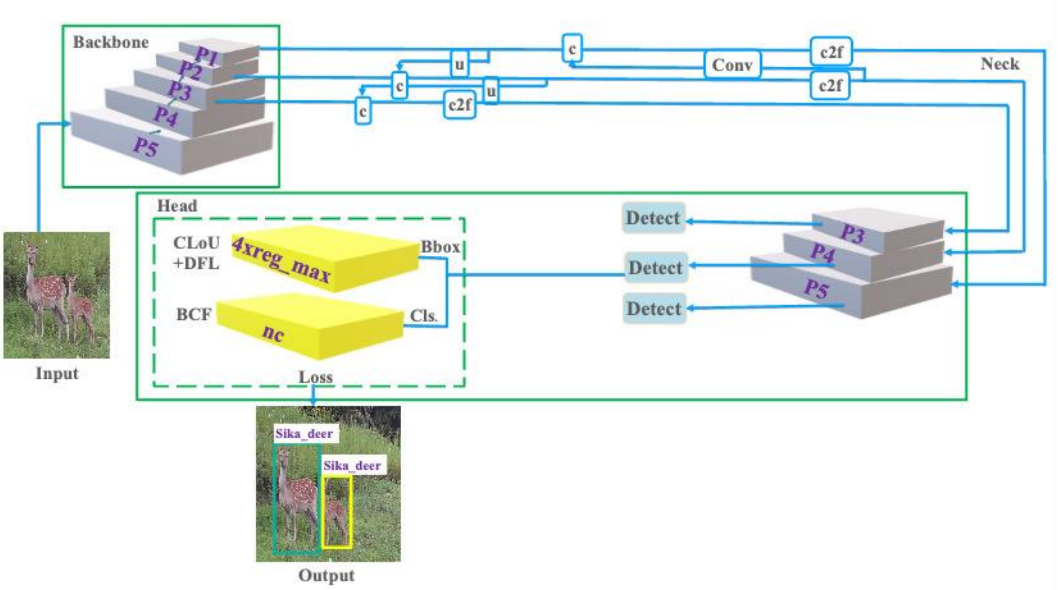
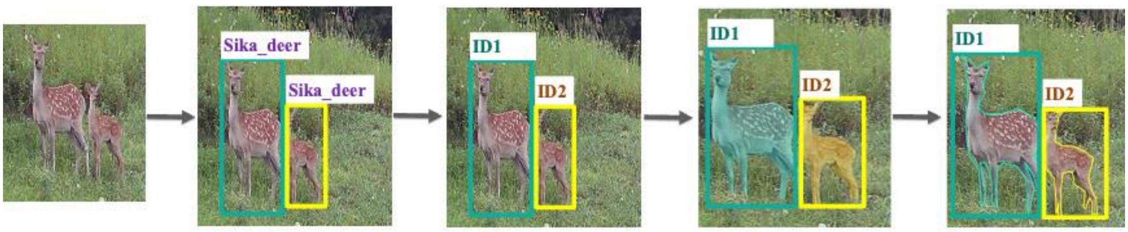


Fig. 3. Yolov8 architecture for Sika deer detection



A. Original frame | B. Object detection | C. Tracker | D. Segment Anything | E. Contour

Fig. 4. Different deep learning ensembled techniques used for Sika deer individual identification.

2.2.3. Segment-Anything Module

We utilize the Segment Anything model to outline the Sika deer within bounding boxes generated by object detection and tracking. This process produced segmentation masks with precise pixel-level accuracy, capturing intricate details of their shapes and features [11]. By assigning distinct colored masks based on tracker IDs, we ensure easy differentiation of individual deer instances within the video. This color-coded segmentation helped in visual identification and facilitated subsequent analysis and tracking of deer movement. Through this segmentation technique, we effectively isolate and extract the features of each Sika deer, contributing to wildlife research, conservation efforts, and ecosystem management initiatives (Fig. 4).

2.3. Feature Extractions

We generated contours for each mask and extracted different features from within the contour portions of individual Sika deer. Contours were created to outline the boundaries of the mask applied to individual Sika deer within images simultaneously isolating the Sika deer from the background, allowing for the extraction of various features exclusively from the Sika deer regions (Fig. 4). These features include statistical measures such as mean and standard deviation across all three colors channel, as well as texture descriptors like smoothness, brightness, and contrast. Additionally, we captured geometric attributes such as area of convex hull, eccentricity along with major and minor axes, perimeter, and solidity. All features were extracted in terms of pixels [12]. These features were obtained from both day and night frames, capturing Sika deer at various distances from the camera trap`s deployment center, aiming to mitigate bias for each individual Sika deer.

2.3.1. Color Channels

We obtained the mean and standard deviation values for all three colors channels within the contour region, a widely used technique in computer vision applications. The mean signifies the average intensity across each color channel (red, blue, and green), while the standard deviation indicates the degree of variation in pixel intensities within each channel (Fig. 5). By extracting these features, we captured crucial statistical insights into the distribution of pixel intensities within the contours of each individual Sika deer.

2.3.2. Texture

We utilized the Laplacian operator to derive the smoothness value within the contour region of each masked Sika deer, illustrating the rapid intensity changes. This measure was performed after Gaussian smoothing, enhancing the robustness of the process. Gaussian smoothing was executed to refine smoothness, since the Laplacian smoothness tends to be more noise-sensitive, necessitating preprocessing (Fig. 5). Additionally, we computed the brightness value for each masked Sika deer based on the mean intensity, and the contrast was assessed by calculating the standard deviation of pixel intensities.

2.3.3. Geometric Attributes

A convex hull was constructed, and its pixel area was computed for each masked Sika deer. The calculation of convex hulls is important in computer vision as it provides spatial information regarding the extent of the species in images, facilitating automated tracking [13]. Moreover, the major and minor axes were computed from the eccentricities of each masked Sika deer. These eccentricities, along with the major and minor axes, serve as essential parameters in Sika deer identification, offering geometric features that differentiate individuals based on variations in body shape and proportions (Fig. 5). Additionally, computing the major and minor axes from eccentricities enhances the characterization process by supplying additional quantitative data on size and orientation, thus enabling more precise and reliable identification of individual Sika deer within a population.

Furthermore, area, perimeter, and solidity were computed for each masked Sika deer to provide supplementary quantitative metrics for individual identification and characterization. The area of each masked Sika deer was computed using “cv2.contourArea” module, while the perimeter was calculated using the “cv2.arcLength” module. Solidity, derived from the mask area divided by the convex hull calculation, offers insights into the overall size, shape, and compactness of the individual Sika deer within the frame, aiding in differentiation based on variations in body dimensions and contours (Fig. 5).

Moreover, these measurements of area, perimeter, and solidity serve as valuable information for population monitoring, ecological studies enabling researchers to track changes in deer demographics and population dynamics over time. Simultaneously, contributing to informed decision-making regarding wildlife conservation and management strategies.

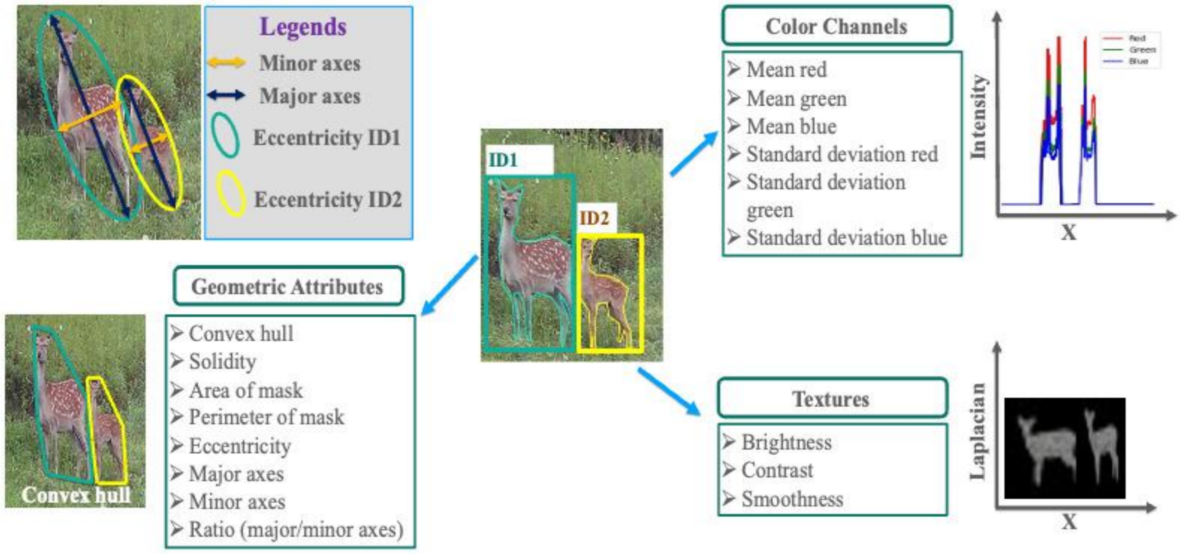


Fig. 5. Different techniques used for feature extractions.

2.4. Machine Leaning Algorithm

2.4.1. Data Filtration

We automated the extraction of all above mentioned features from each masked Sika deer and saved them based on tracker ID for each video. This process was repeated for all videos. However, the features of the same Sika deer across videos, were compiled manually. The features of each Sika deer were organized into seven separate files, with the individual unique ID serving as the class labels.

During this compilation process, we filtered the datasets based on the frame numbers of the video captured and the frame number saved in files. Datasets of Sika deer that were indistinguishable or whose full bodies were not captured were removed. Subsequently, from the seven individual files, we extracted a total of 2799 datasets for further analysis. Among these, 20% of the datasets were reserved for testing purposes, while the remaining 80% were allocated for training.

2.4.2. Variance Inflation Factors (VIF)

We conducted VIF testing to assess the correlation among the extracted features. Our analysis revealed significant multicollinearity in the features (VIF > 10), indicating least variance within our datasets (Table 1). High multicollinearity diminishes the precision of the model and can pose challenges when directly fitting the datasets into the SVM model.

2.4.3. Principal Component Analysis (PCA)

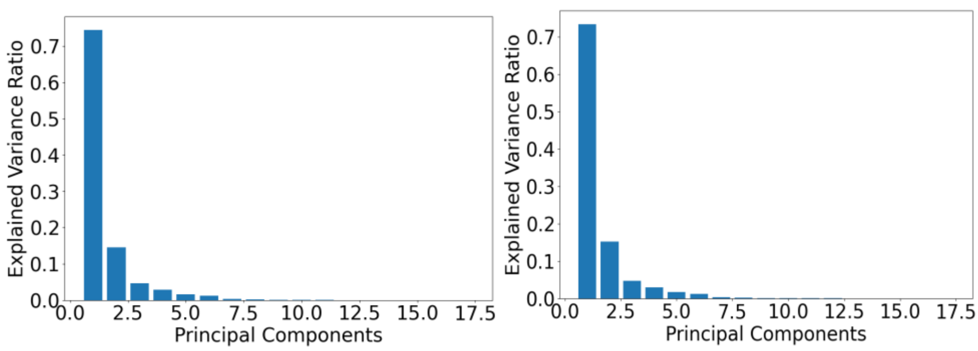
In order to mitigate the multicollinearity present in the collected datasets, we conducted PCA (Principal Component Analysis) prior to passing into the SVM model. Through the component analysis, we observed that PCA1 and PCA2 collectively accounted for over 80% of the variance in both the training and testing datasets (Fig. 6). Consequently, we choose to feed PCA1 and PCA2 into the SVM model for further analysis.

2.4.4. Support Vector Machine (SVM)

We utilized PCA1 and PCA2 as inputs for SVM to identify individual Sika deer and determine decision boundaries that effectively separate classes. SVM is renowned for its application in classification tasks, capable of creating both linear and non-linear decision boundaries. Moreover, SVM exhibits robustness to outliers and prioritizes support vector for analysis.

Table 1. Variance Inflation Factor values for all extracted variables.

S.N	Variables		VIF
1	**Color channels**	Mean red	1.56e+08
2		Mean green	2.35e+08
3		Mean blue	1.29e+07
4		Standard deviation red	9.63e+07
5		Standard deviation green	1.90e+08
6		Standard deviation blue	1.83e+07
7	**Textures**	Brightness	9.61e+08
8		Contrast	6.66e+08
9		Smoothness	2.41e+02
10	**Geometric attributes**	Convex hull	5.36e+02
11		Solidity	1.06e+01
12		Area of mask	2.16e+02
13		Perimeter of mask	1.43e+02
14		Eccentricity	2.95e+00
15		Major axes	1.48e+01
16		Minor axes	2.08e+02
17		Ratio (major/minor axes)	3.95e+01



a) Training datasets
b) Testing datasets

Fig. 6. PCA for both training and testing datasets.

2.4.4.1. OneVsRest SVM classifier

While SVM was originally intended for binary classification tasks, our field study identified seven individual Sika deer, necessitating a multi-classification approach. We employed the OneVsRest SVM classifier, specifically designed for multi-classification tasks. This classifier operates similarly to a binary classification model but is capable of handling multiple classes. In the OneVsRest SVM classifier, each class of individual Sika deer was trained to be predicted as positive, while other classes were considered negative [14].

2.4.4.2. Kernels

Different kernels are available for SVM classifiers. Linear kernels (linear) are primarily used for predicting linear combinations of input features, effectively separating datasets with straight lines. Polynomial kernels (poly) are suitable for non-linear datasets, employing degree parameters (d) to find optimal values for each dataset. The Radial Basis Function (rbf) kernel operates based on K-nearest neighborhood similarly, ideal for classifying datasets that are not linearly separable, known for its high performance. Lastly, the sigmoid kernel (sigmoid) originates from neural networks and is complex in structure but less widely used due to less-than-ideal backpropagation [14].

Selecting suitable kernels for individual Sika deer identification poses a challenge. Thus, we computed a 5-fold Cross Validation Score on the training datasets. This involved splitting the training datasets into five parts (part 1, part 2, …., and part 5) to build five different models, enhancing confidence in our algorithm`s performance. The accuracy score derived from the 5-fold cross-validation provided insights into the appropriate kernel types to be used for our datasets (Fig. 7).

2.4.4.3. Hyperparameters Tuning

In our datasets, we established two hyperparameters (gamma and C) that required careful tuning to prevent overfitting and underfitting. Gamma influences the complexity of the decision boundary created by the SVM model. A small gamma value results in a smoother decision boundary, potentially causing underfitting, whereas a high gamma value creates a more complex decision boundary, potentially leading to overfitting. Similarly, C serves as a regularization parameter, where a smaller C value generates a smoother decision boundary, potentially causing underfitting, while a higher C value produces a more rigid decision boundary, potentially causing overfitting in the datasets [14]. Therefore, it is essential to carefully tune gamma and C hyperparameters to fit the dataset properly.

To achieve this, we utilized the GridSearchCV library and experimented with various values of gamma and C, focusing on achieving a Mean Test Score of 0.99 (Fig. 8). After each adjustment of gamma and C, we assessed the performance metrics of both the training and testing datasets to determine whether the datasets were underfitted, overfitted, or properly fitted. This iterative process allowed us to optimize the hyperparameters effectively and ensure the robustness of our model.

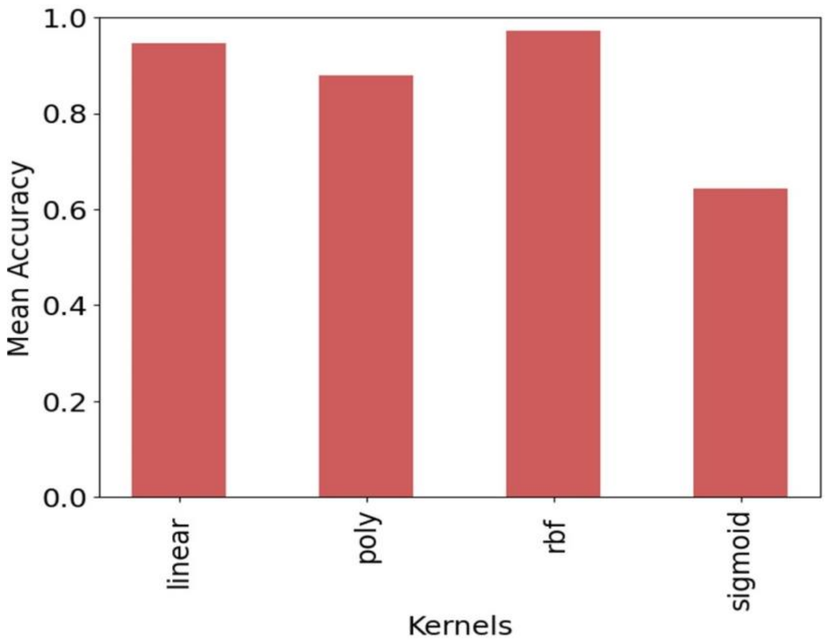


Fig. 7. 5-Fold Cross Validation Score accuracy values for the kernels

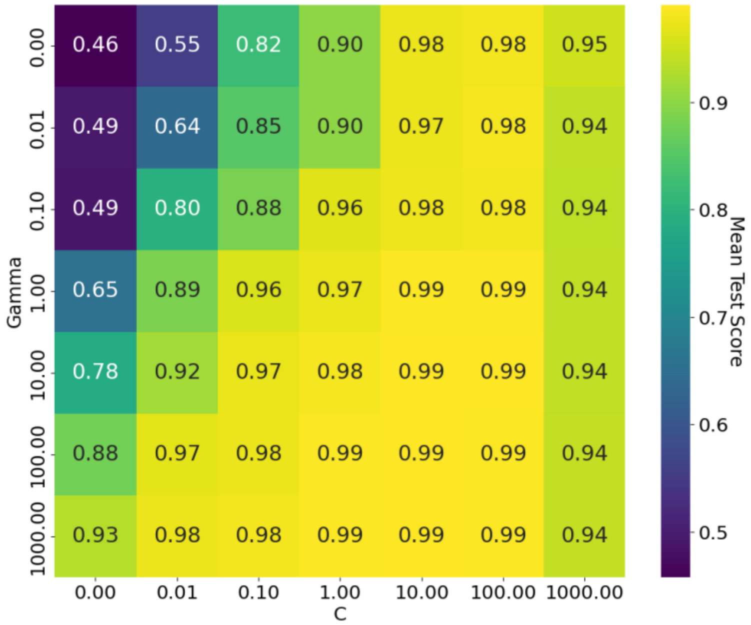


Fig. 8. Mean Test Score for tuning gamma and C

2.4.4.4. Performance metrics

We performed different performance metrics for testing the performance of our model. Confusion metrics provide the information of true positive (TP: model predicted as true outcome and actual observation was also true), true negative (TN: model predicted as true outcome but the actual observation was false), false positive (FP: model predicted as false outcome while the actual observation was true), and false negative (FN: model predicted as false outcome while actual observation was also false) that provides overall effectiveness in multiclass classification that is suitable for both even and uneven distribution of the datasets.

We computed various metrics to assess the performance of our model. Accuracy, a widely used measure, is calculated as (TP + TN) / (TP + FP + FN + TN). Precision, another important metric, is defined as TP / (TP + FP), representing the proportion of true positives among all positives predicted by the model. Recall, on the other hand, measures TP / (TP + FN), indicating the proportion of true positives among all actual positive outcomes. Additionally, we calculated the F1-score, which signifies the balance between precision and recall and is expressed as: 2 * (precision * recall) / (precision + recall), where precision (p) and recall (r) are used. To visualize the model`s performance comprehensively, we employed the Area Under the Curve of the Receiver Operating Characteristics (AUC-ROC) curve. This curve illustrates the relationship between TP and FP.

3. RESULTS

We observed seven individual Sika deer in our field study captured by three camera traps. The results of the implemented Yolov8n model demonstrated a precision exceeding 0.95 in detecting Sika deer, along with a recall surpassing 0.92 (Fig. 9). Furthermore, during the Cross Validation Score analysis to determine the appropriate types of kernels for our datasets, it was revealed that the rbf kernel yielded the highest suitability, with a mean accuracy score of 0.97. Likewise, during experimentation with various hyperparameters such as gamma and C using cross-validation scores, we identified a gamma value of 10 and a C value of 100 to be well-suited for our datasets.

We examined the confusion matrix of both the training and testing datasets generated by the OneVsRest SVM classifier, and we found that it accurately identified and distinguished seven individual Sika deer instances from the dataset (Fig. 10).

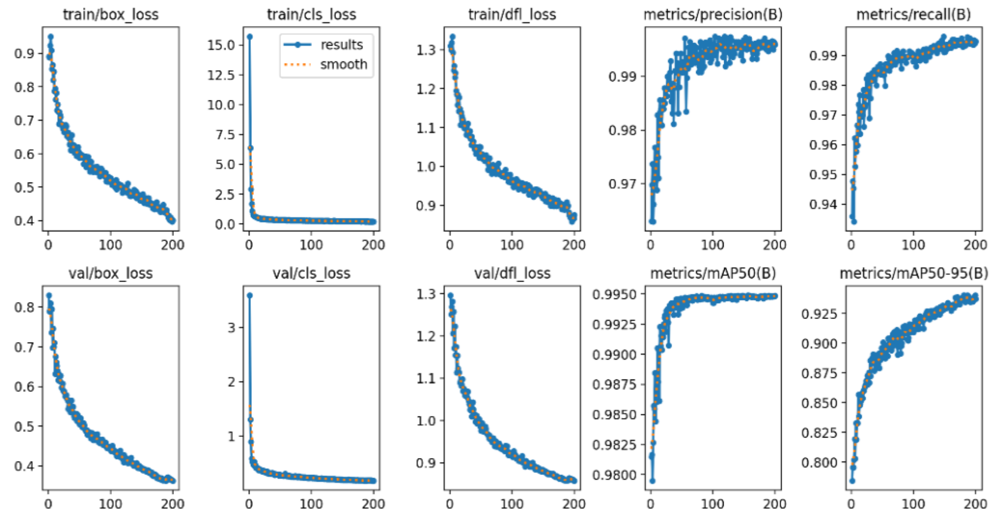
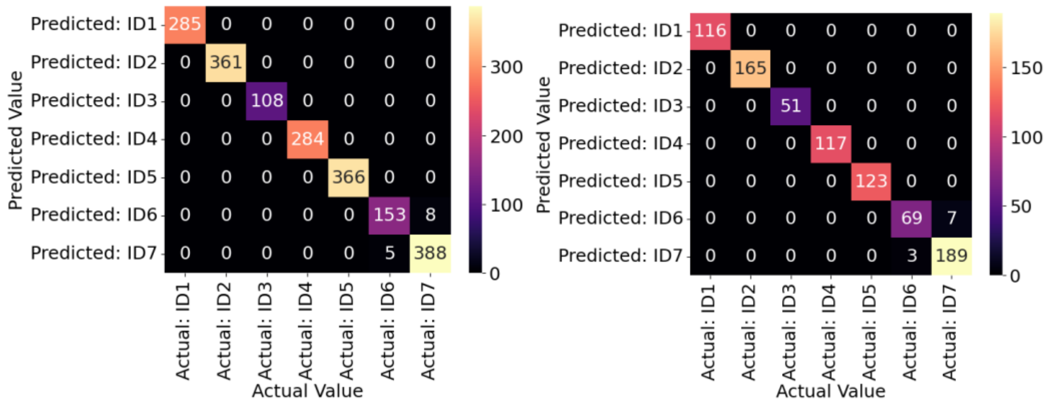


Fig. 9. Results of Yolov8 model architecture for Sika deer detection.



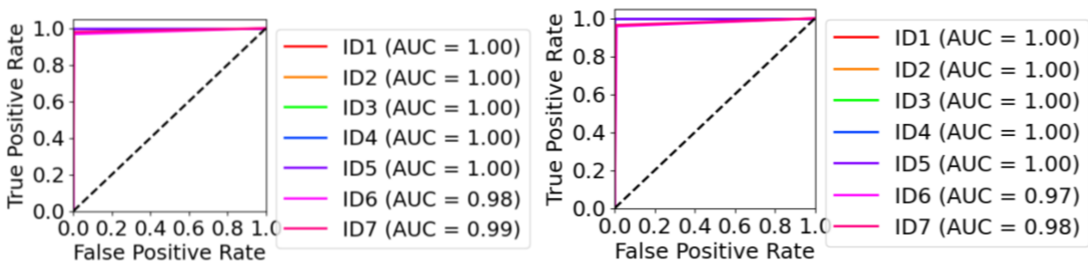
a) Training datasets b) Testing datasets

Fig. 10. Confusion matrix generated by OneVsRest SVM classifier.

We also evaluated the result of SVM classifier computing the accuracy for both the training and testing datasets and found that the value for both the training and testing datasets was 0.99 which, suggesting the datasets fitted well. The precision, recall, and F1-score for all seven individual Sika deer for both training and testing datasets was also over 0.9 suggesting better performance by our proposed classifier in classification of individual Sika deer (Table 2). The AUC-ROC curve generated by the above SVM classifier also provided impressive results with the AUC value for all individual Sika deer of over 0.9 for both training and testing datasets (Fig. 11). We finally created the decision boundary using gamma and C as hyperparameters for both training and testing datasets classifying individual Sika deer (Fig. 12).

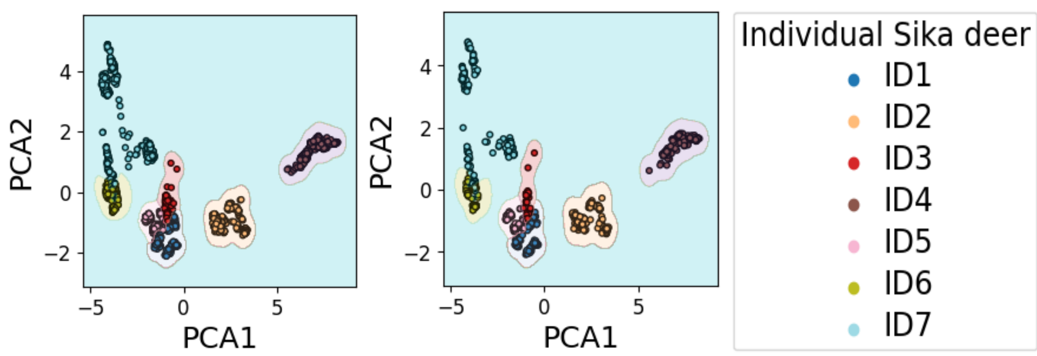
Table 2. Evaluation of the SVM model through various performance metrics.

Individual	Precision		Recall		F1-score	
	Training	**Testing**	**Training**	**Testing**	**Training**	**Testing**
ID1	1.00	1.00	1.00	1.00	1.00	1.00
ID2	1.00	1.00	1.00	1.00	1.00	1.00
ID3	1.00	1.00	1.00	1.00	1.00	1.00
ID4	1.00	1.00	1.00	1.00	1.00	1.00
ID5	1.00	1.00	1.00	1.00	1.00	1.00
ID6	0.95	0.91	0.96	0.96	0.93	0.93
ID7	0.99	0.98	0.96	0.96	0.97	0.97
Accuracy					0.99	0.99
Macro Averaging	0.99	0.98	0.99	0.99	0.99	0.99
Weighted Averaging	0.99	0.99	0.99	0.99	0.99	0.99



a) Training datasets　　a) Testing datasets

Fig. 11. AUC-ROC curve generated by OneVsRest classifier.



a) Training datasets　　b) Testing datasets

Fig. 12. Decision boundaries generated by OneVsRest SVM classifier.

We moreover tested on a single unseen video which were not included (for training and testing the model) on this model, which encompasses object detection techniques, feature extraction, SVM classification via segment anything and tracker modules, demonstrating promising performance. Here, green color represented the prediction made by model as true as actual while red represented prediction was false the actual (Fig. 13).

4. DISCUSSION

Accurately identifying individual Sika deer is crucial for effective management practices and understanding their interactions with humans. In this study, we focus on automating the identification process for Sika deer. Most of the research indicates that the Yolov8 architecture for object detection outperforms other versions of yolo architectures in terms of both performance and latency [15]-[16]. Specifically, we found that the Yolov8 architecture, implemented using the Nano framework, is well-suited for identifying and localizing Sika deer with a precision exceeding 0.95.

To track the movement of individual Sika deer in videos, we employed DeepSort tracker, which assigns unique IDs to each deer. This tracking method enhances our ability to analyze visual data, resulting in improved performance even in challenging scenarios [17].

Segmenting objects in images traditionally requires significant time and effort [11]. However, in our research, we used an automatic segmentation approach for Sika deer using a segment anything module based on created bounding boxes with tracker. This method effectively masks individual Sika deer within their respective bounding boxes, streamlining the segmentation process. This method proves effective by providing pixel-level accuracy and significantly reducing the time required for segmentation [11]. Automating the segmentation process for masking individual Sika deer ensures efficiency and precision in the analysis, enabling the extraction of features from each masked Sika deer.

We have observed multicollinearity among various extracted features, presenting a challenge when passing these datasets directly into the SVM classifier. Multicollinearity diminishes the variance in datasets, resulting in minimal variance or even none within the datasets, potentially leading to overfitting or underfitting of the model [18]. To address this issue, we employed PCA, a widely recognized technique known for its ease of use. PCA not only resolves multicollinearity issues but also facilitates dimension reduction [18]. In our study, PCA1 and PCA2 accounted for over 80% of the variance in our datasets. Consequently, we exclusively utilized these two components as inputs for the SVM classifier.

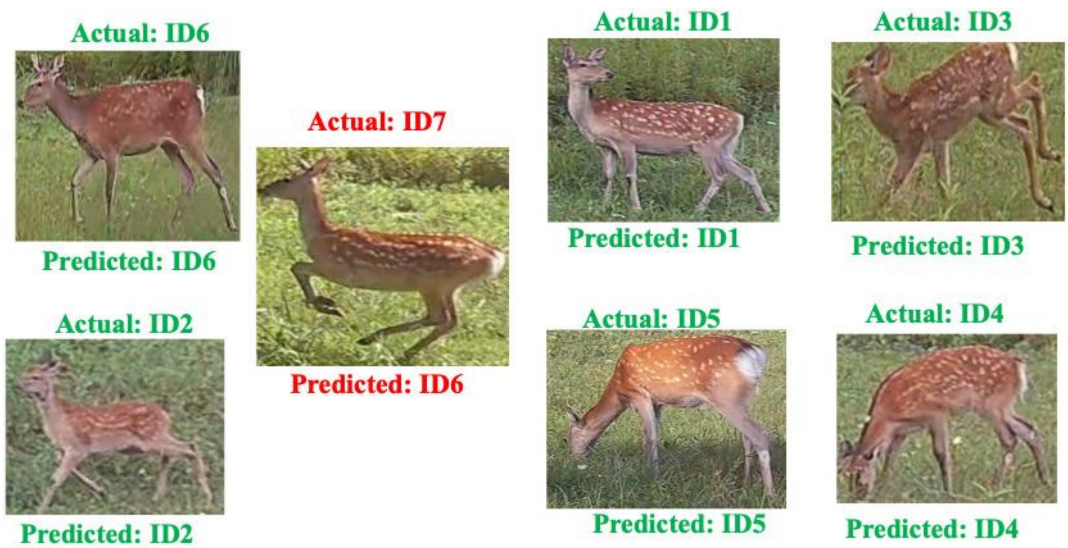


Fig. 13. The model prediction on unseen datasets.

We emphasized the utilization of the SVM classifier due to its capacity to create decision boundaries suitable for both linear and non-linear datasets, while also maintaining precision even with unbalanced datasets [14]. Initially designed for binary classification problems, the SVM classifier has been extended to support multiclass classification tasks. In this study, we employed the OneVsRest SVM classifier, given that our field study identified seven individual Sika deer. This classifier operates similarly to a binary classification model used purposely for multiple classes. Within the OneVsRest classifier framework, each sika deer is trained to be recognized as positive, while all other classes are treated as negative [14].

Among the kernels considered for the OneVsRest SVM classifier, the rbf kernel proved to be suitable in our case, as assessed through 5-fold cross-validation with a mean accuracy of 0.97 (Figure 7). Similarly, employing the GridSearchCV library to fine-tune the gamma and C values, two hyperparameters exclusively utilized for the OneVsRest SVM classifier with the rbf kernel, we determined that a gamma value of 10 and a C value of 100 were optimal for our extracted features datasets (Figure 8). The adoption of 5-fold cross-validation score computation and the GridSearch Library for hyperparameter tuning are widely acknowledged methodologies to effectively fit the datasets to the model [14].

Throughout our investigation, we employed a range of performance metrics to evaluate the SVM classifier on both training and testing datasets. The results indicated that the classifier achieved precision, F1-sore, recall, and accuracy metrics exceeding 0.90 overall. These findings highlight the classifier effectiveness in accurately identifying the individual Sika deer, an important aspect of its performance assessment.

This study marks a significant step forward in individual Sika deer identification through the integration of deep learning and machine learning methodologies. However, it is important to acknowledge several limitations. Firstly, the approach was applied to only seven individual Sika deer, this constraining the generalizability of the findings regarding model performance on a larger scale. We recommended an expansion of this research to encompass the large number of Sika deer population. Secondly, while the study utilized both deep learning and machine learning techniques and extracted features in a broadly applicable manner, we propose exploring the identification of Sika deer exclusively through deep learning methods, such as facial recognition architecture, as demonstrated in other species like zebra and salamander. We also suggested adopting this approach for studying the individual identification of both terrestrial and aquatic animals, as well as plants, due to its ease of implementation. The study utilized Sika deer videos captured during both day and night from three camera traps installed for 60 days during summer. However, this may not capture the full variability present in the datasets. Therefore, we suggest deploying multiple camera traps over extended periods to encompass diverse environmental conditions.

5. CONCLUSION

In conclusion, our study employed the Yolov8 architecture within the Nano framework, achieving a precision exceeding 0.95. We identified seven individual Sika deer, extracting 17 features from the masked deer generated by the segmented anything modules within the bounding box and tracker. Due to multicollinearity in our datasets (VIF > 10), we conducted PCA, utilizing PCA1 and PCA2, which accounted for over 80% of the dataset`s variance, as input for the OneVsRest SVM classifier. This classifier was chosen for its ability to handle multiple classes. Employing rbf kernels, we attained a mean accuracy of 0.97 through 5-fold cross-validation. Utilizing the GridSearchCV library, we determined that a gamma value of 10 and a C value of 100 were optimal for our datasets. Evaluation metrics, including precision, recall, F1-score, and overall accuracy, all surpassed 0.90 for both training and testing datasets, underscoring the model`s robustness and reliability in individual Sika deer identification.

ACKNOWLEDGEMENTS

We express our gratitude for the support provided by the Project base AI (PBL-AL) program and the Ministry of Education, Culture, Sports, Science, and Technology (Monbukagakusho: MEXT) scholarship granted to Sandhya Sharma and Suresh Timilsina.

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