IT'S OTTERLY CONFUSING – DISTINGUISHING BETWEEN FOOTPRINTS OF THREE OF THE FOUR SYMPATRIC ASIAN OTTER SPECIES USING MORPHOMETRICS AND MACHINE LEARNING

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ABSTRACT

*Southeast Asia is home to four sympatric otter species: Eurasian otter (*Lutra lutra*), Asian small-clawed otter (*Aonyx cinereus*), smooth-coated otter (*Lutrogale perspicillata) *and hairy-nosed otter (*Lutra sumatrana*). All species are on the IUCN's Red List of Endangered Species. In many regions, there is an overlap in the distributions of at least two species. To establish population size and range of these elusive animals, a variety of non-invasive data collection methods is available. Footprints often tend to be overlooked as valuable scientific data, which potentially leads to a wealth of information being lost.*

The Footprint Identification Technology (FIT), developed by WildTrack, analyses morphometric data extracted from digital images of footprints and uses state-of-the-art Machine Learning models for classification tasks. In this study, we aimed to develop algorithms to distinguish between three of the four otter species of southeast Asia (Lutra lutra, Aonyx cinereus *and* Lutrogale perspicillata)*, using footprints.*

For the three species, a digital footprint image database of known otters was developed with the help of several zoos. Using specific features, landmark points were placed on each footprint image and morphometric measurements in the form of distances, angles and areas were extracted and analysed in JMP software. The average classification accuracy for discriminating between the three species, using multiple analytical methods, was 97%. It is planned to develop this technology further adding the fourth species (Lutra sumatrana) *and aim for sex and individual classification, for which more footprint data are necessary. The authors welcome contributions of footprint images from known animals.*

Keywords: *Eurasian otter,* Lutra lutra, *Asian small-clawed otter,* Aonyx cinereus, *smooth-coated otter,* Lutrogale perspicillata, *hairy-nosed otter,* Lutra sumatrana, *Footprint Identification Technology, Footprint, Track, XGBoost*

INTRODUCTION

The development of effective conservation strategies requires reliable information on species distribution, population sizes and composition **(Conde et al., 2019)**. These data, however, are often hard to get, especially for elusive and predominantly aquatic animals like otters.

There are four otter species with an overlapping distribution range in Asia: the Eurasian otter (*Lutra lutra*), the Asian small-clawed otter (*Aonyx cinereus*), the smooth-coated otter (*Lutrogale perspicillata*) and the hairy-nosed otter (*Lutra sumatrana*). Each species has an IUCN protection status, with the hairy-nosed otter being the most endangered species of the four **(Duplaix and Savage, 2018)**.

There are several regions in southeast Asia where at least two of the four species are sympatric **(Yoxon and Yoxon, 2017)**. It can be difficult to distinguish between the species visually and it is therefore critical to have reliable monitoring tools available. Wherever possible, non-invasive methods should be deployed to minimise disturbance and potential harm to the animals whilst ensuring the reliability and quality of data collected **(Jewell, 2013)**.

Traditional tracking of animals can be seen as a non-invasive approach. Animal tracks can be collected without any disturbance to otter populations and used to inform on numbers and distribution. Data based on animal tracks is also reliable and cost-effective if the tracker has the required skills **(Evans et al., 2009)**.

Liebenberg (2021) called tracking 'the origin of science' and with the vast development in scientific data collection and computer-assisted analysis **(Petso et al., 2022)**, morphometric footprint analysis opens up new possibilities in wildlife monitoring. Another great advantage in using tracks as a data source for wildlife monitoring, is that indigenous communities with traditional ecological knowledge (TEK) can be involved in wildlife conservation research. Such collaborations can be of benefit to everyone involved and add valuable data for wildlife monitoring **(Vieira et al., 2015; Ramos et al., 2016)**. In order to use tracks as a reliable data source, a strict protocol in data collection and analysis is crucial.

The Footprint Identification Technology (FIT) developed by WildTrack (www.wildtrack.org), combines traditional tracking with modern Machine Learning classification algorithms **(Li et al., 2018)**. Following a strict protocol, it allows researchers, who might not be expert trackers, to draw dependable and unbiased information. FIT has been successfully developed for a wide range of endangered species and can classify species **(Alibhai et al., 2008)**, sex **(Alibhai et al., 2017)**, age class **(Li et al., 2018)** and individual ID **(Alibhai et al., 2008; Jewell et al., 2016; Alibhai et al., 2017; Li et al., 2018)** once species-specific algorithms have been developed.

FIT classification accuracies are typically over 90% **(Petso et al., 2022)**. In order to build such models, a reference database comprising images of known individuals, sex and/or species of a sufficient size and quality is required. Such databases are often created with the help of ex-situ organisations.

In this pilot study, we investigated the use of FIT to predict three Asian otter species based on morphometric features of their footprints. We deployed two different prediction models, Stepwise Linear Discriminant Analysis (LDA) and XGBoost.

LDA has often been the method of choice in comparable footprint studies of other species **(Sharma et al., 2005; Alibhai et al., 2008; Alibhai et al., 2017; Li et al., 2018)**.

XGBoost is a supervised Machine Learning technique library that uses scalable, gradient boosting decision trees. It is often referred to as the best algorithm for classification and regression tasks of tabular data and has been the most successful method for the Machine Learning competition site “Kaggle” **(Chen and Guestrin, 2016)**.

To the best of our knowledge, this is the first study that implements Machine Learning algorithms to classify otter species using biometric measurements from footprints as input data. In this report, we want to highlight the possibility of developing unbiased models with high accuracy. In addition, we investigate which features are the most important for these models in order to share insights of important areas of a footprint when species classification in situ is desired.

We would also like to encourage researchers to implement this monitoring tool in the field and help improve the classification capability and robustness of this method by contributing otter tracks to our otter footprint database.

METHODS

Technical drawings

Figure 1 shows technical drawings of otter tracks of the three species investigated in this study. The drawings are based on footprint images received for this research as well as photos of the underside of the three species' feet. Track drawings give the tracker as much detail as possible to interpret a track found in the field, but it is rare to find a track with all the components shown in the drawings. Tracks can vary in size, shape and detail depending on substrate and gait of the animal **(Elbroch, 2019)**. As a result, certain parts of the otter’s feet often do not register well in the track and the drawings reflect this by showing these parts in light grey.

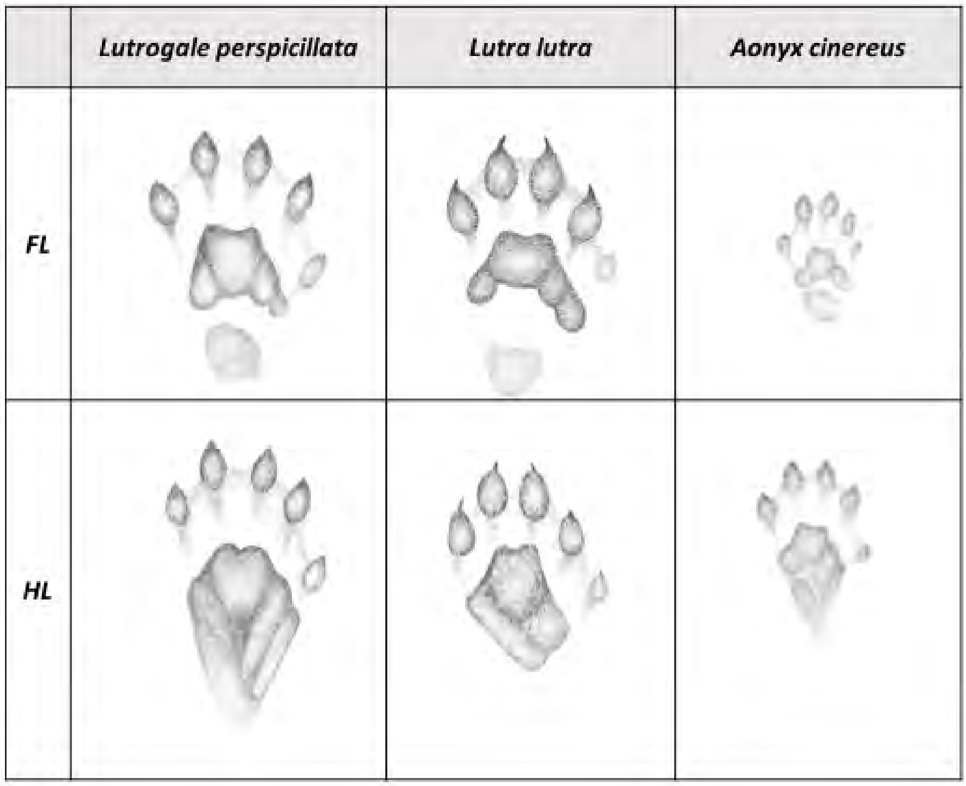

Figure 1. Technical drawings of tracks of three otter species. FL = Front Left; HL = Hind Left; Illustrations and copyright by Asaf Ben-David.

Description of the tracks by species are as follows:

- Smooth-coated otter (*Lutrogale perspicillata*): - The general impression is of a large, elongated otter track. The claws are short and blunt in comparison to the Eurasian otter. The toes are oval, and the bones between the toes and metacarpal or metatarsal pads are long and register clearly. Toe 1 (thumb) is almost straight below toe 2. The negative space between the toes and the metacarpal or metatarsal pad is 1.5 - 2 times the toe pad size. The metacarpal pad is wide and has a clear saddle in the centre top of the pad. The metatarsal pad is almost twice the size of the metacarpal pad.
- Eurasian otter (*Lutra lutra*) - The front track is less asymmetrical than the hind track and not as elongated as for smooth-coated and Asian small-clawed otters. The claw marks are small, sharp, and clear. The toe marks are large with a clear teardrop shape. The front foot’s carpal pad is rounded and out of the three species it shows the most negative space to the metacarpal pad.
- Asian small-clawed otter (*Aonyx cinereus*) – This is the smallest track of the three species. The claws are very short and therefore mostly absent from the track. The toes are oval. The front foot is elongated and the carpal pad has a distinct angle towards toe 5.

Generally, the difference between these three otter species is more apparent in the front tracks than in the hind.

It was important to learn as much as possible about the footprint anatomy of these three otter species to decide on the landmark point placement for feature extraction. It was further important to compare these perfect anatomical diagrams with real footprint images to decide which footprint images were of sufficient quality for the study.

Otters leave typical mustelid tracks, which show five toes, a segmented metacarpal (palm on the front foot) and metatarsal (palm on the hind foot) pad. The front feet also have a separate carpal (heel) pad while the hind feet are clearly elongated, but do not show the same separation of metatarsal and tarsal (heel) pads. The otter species in this study all have claws, although as its name suggests the claws on the Asian small-clawed otter are small and often do not show in a print. They all have webbing between the toes and a wide gap (negative space) between toes and meta pads. The heel pad as well as webbing and toe 1 (thumb) often do not register well in the track and are difficult to see for the untrained eye, which is one of the reasons why otter tracks can be mistaken for canine tracks **(Rhyder, 2021; Grolms, 2021)**. Figure 2 shows the numbering of toes in otter tracks as well as clearly labelled metacarpal, carpal and metatarsal pads.

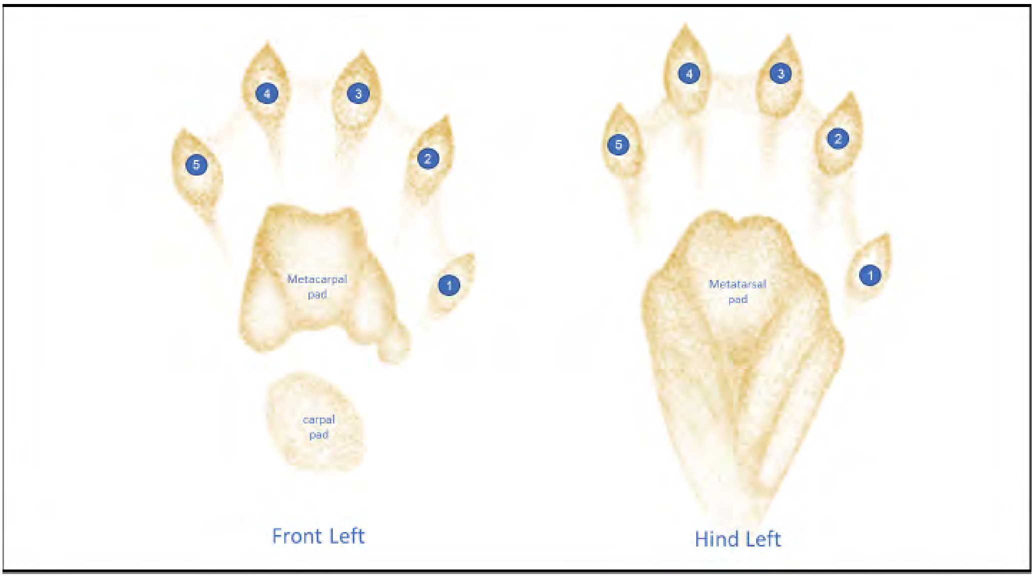

Figure 2: Illustration of otter left front and hind footprints with the appropriate labels for toes 1 to 5, metacarpal, carpal and metatarsal pads.

This shows how complex tracks and tracking are and to evaluate photographs of footprints can even be more challenging. In the field, well-trained trackers have a lot more information available than can be found in a photograph and they are able to take gait and behavioural signs, such as movement through habitat and sprainting behaviour, into consideration for species classification. For most wildlife conservationists who lack such training this is not an option, but we show here that images of footprints can be analysed and are a very valuable data source, which provide a non-invasive tool for otter surveys and monitoring.

Data collection

Footprint images were collected following WildTrack's standardised footprint collection protocol for FIT (see Appendix) at eight zoos (six U.K., two Germany) by either the zoo staff or the researchers themselves. Several zoos have groups of otters in their enclosures, where keepers find it difficult to identify individuals. However, for the present study we focussed on classification at species level only, so individual identification of otters was not necessary.

To improve footprint quality, where possible, sand patches were created in the enclosures. However, prints found in muddy substrate were also included in the study. Each footprint was then photographed with a metric ruler for scale. Figure 3 shows footprint image examples of the three otter species, which show a variety of substrates and footprint qualities included in this study.

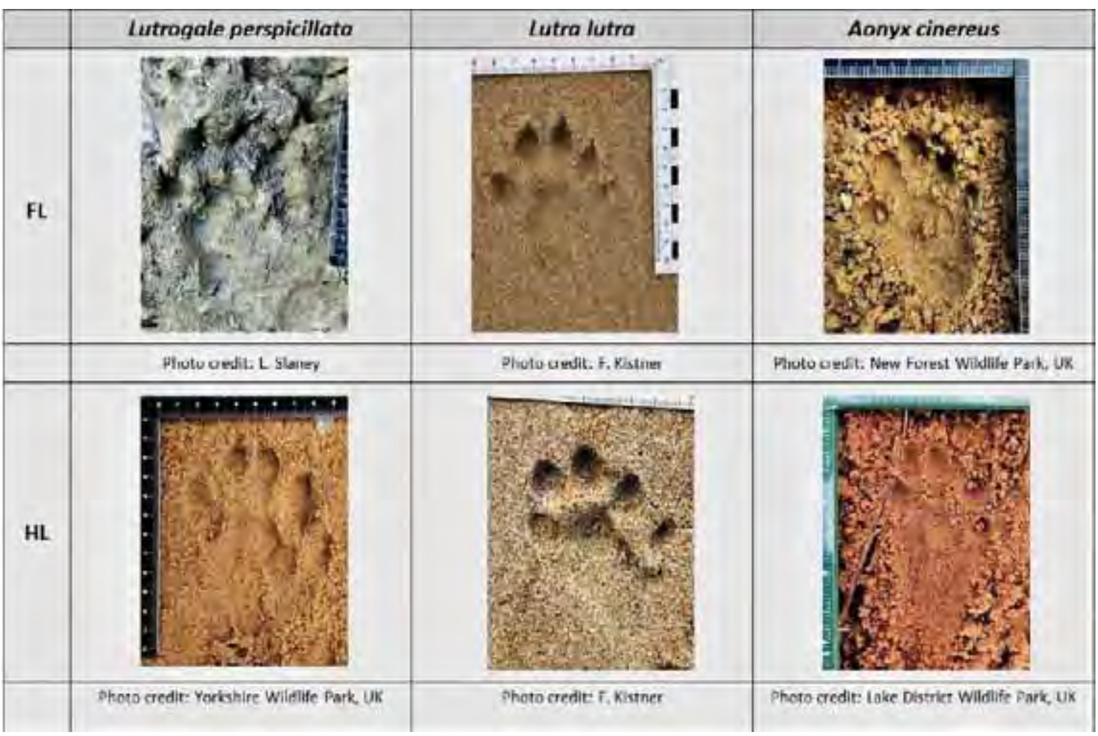

Figure 3. Examples of otter footprints of different quality and in a variety of substrates, which were used for the study. Note: FL = Front Left; HL = Hind Left;

The analysis is based on 100 footprint images for each species. Because of the large group size at some of the otter enclosures, we were only able to estimate a range of the number of individual otters which contributed data to the study (Table 1).

Table 1: Range of individuals per species contributing data

Species	Range of individuals in study
Eurasian otter (*Lutra lutra*)	**10-18**
Asian small-clawed otter (*Aonyx cinereus*)	**8-13**
smooth-coated otter (*Lutrogale perspicillata*)	**6-16**

Image processing

All subsequent image processing and statistical analyses were carried out in JMP 16.2 Pro version. The add-in, XGBoost, created for JMP software **(Wolfinger, 2020)** was additionally installed.

Following a standardised protocol, 300 footprints (100 per species) were analysed. This process comprises alignment and orientation of the image, calibration of scale and the manual placement of 11 specific anatomic landmark points (Figure 4). We used hind and front feet and aimed to define points that are consistently found in front and hind feet among all three species. The setting of the landmark points followed the standardised protocol for left feet. Therefore, images of the right feet were flipped horizontally prior to processing to increase the amount of processable footprints. Measurements here are taken at the centre of the toes and the heel pad, as this has proven to be more robust to variation in substrate.

A scripted routine adds a further six derived landmark points and subsequently automatically extracts a morphometric profile. This profile comprises 208 measurements per footprint, consisting of distances, angles, and areas, which is illustrated in Figure 4.

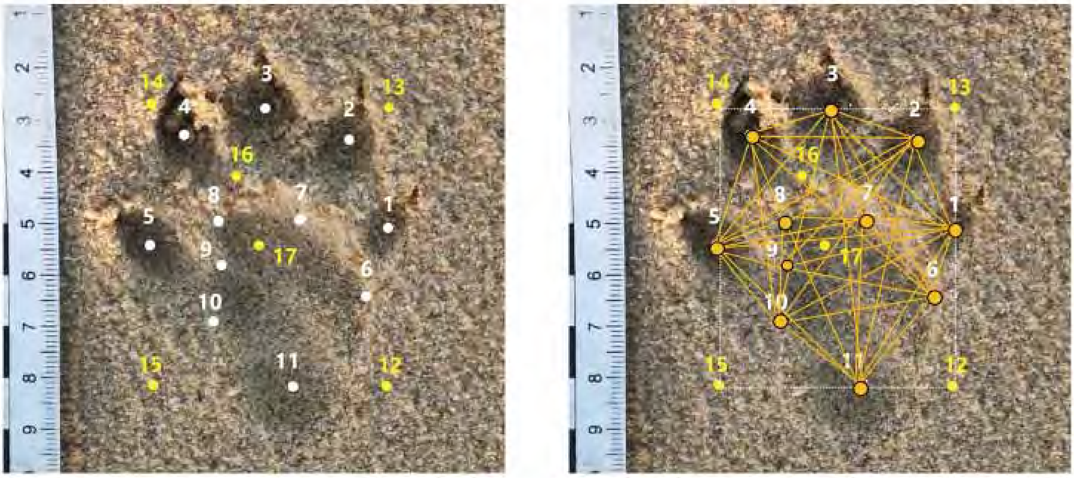

***Figure 4. Image of a left front track from a Eurasian otter* Lutra lutra.**

Left image: Footprints are first aligned at two rotation points at the base of the second and 4th toe and two points on a metric ruler are used for scaling of the image. Afterwards, 11 landmarks (white) are manually placed by a human operator and an additional six points are automatically derived (yellow).

Right image: Geometric profile of a footprint. A total of 208 measurements comprising distances, angles and areas form the morphometric profile of each footprint.

Statistical analysis

Species classification

In a first step, the dataset of the biometric measurements was randomly split into a training set (75% of data) for the model development and a test set (25%) to evaluate the classification capability of the model. The test set was excluded from the model development.

Stepwise forward LDA and XGBoost Classifier were chosen as classification models (classifier) and trained on the training set.

To avoid overfitting of the model, an additional internal k-fold (n=5) cross-validation step was applied during training. Hyperparameters were automatically tuned within the JMP Model screening platform.

The classifiers assign probabilities between 0 and 1 to a class (here 'otter species'). The class with the highest probability is assigned the predicted species.

In a second step, the models with the highest overall classification accuracy (correct number of predictions divided by total number of footprints) in the training process were selected and applied to the test set, which can be seen as new data.

Significance of footprint features ('Feature Importance')

An advantage of using tree-based methods, such as XGBoost, is that the importance of features for the prediction of the model can be evaluated. Often this is done by the calculation of gain scores, with "gain" being defined as the improvement in accuracy brought by a feature to the branches it is on **(Abu-Rmileh, 2019)**. For LDA, Feature Importance can be identified by calculating F-Ratios of the variables **(Gu et al., 2014)**.

We analysed the most important features chosen by the best overall model and investigated how much of the variance of the whole data could be explained when focusing only on the most influential measurements. In order to achieve this, we built a decision tree model with only two splits as a general field assessment recommendation.

RESULTS

Species classification

For the whole dataset, 291 of the 300 images (training and test set) were correctly assigned to its respective species by our final XGBoost model, leading to an overall classification accuracy of 97%. The Linear Discriminant Analysis (LDA) classified 271 prints correctly and therefore had an overall accuracy on the same data of 90%.

XGBoost predicted the Asian small-clawed otter correctly at a rate of 99%, the Eurasian otter at 97% and the smooth-coated otter at 95%. This and the predictions of the LDA are shown in Table 2, which is the confusion matrix of the entire dataset.

The confusion matrix compares the model prediction with the true class (species) of each data point (footprint). A perfect model would only have non-zero values on the main diagonal of the matrix.

Table 2. Confusion matrix of the whole dataset. Each species had one hundred footprints. The confusion matrix compares the true species of a footprint with the prediction of the XGBoost and the LDA classifier

	Prediction XGBoost			**Prediction LDA**		
Species	***Aonyx cinereus***	***Lutra lutra***	***Lutrogale perspicillata***	***Aonyx cinereus***	***Lutra lutra***	***Lutrogale perspicillata***
Aonyx cinereus	**99**	**0**	**1**	**96**	**3**	**1**
Lutra lutra	**1**	**97**	**2**	**1**	**92**	**7**
Lutrogale perspicillata	**1**	**4**	**95**	**3**	**14**	**83**

When looking solely at new data of the test set, the overall accuracy for XGBoost was 91% and 85% for the LDA model. ASCs were predicted with 96% accuracy, Eurasian otters with 92% and smooth-coated with 84% by XGboost and 92% of Asian small-clawed otters, 84% of Eurasian and 80% for the smooth-coated applying the best LDA model (Table 3).

Table 3. Confusion matrix of the test set. The test set comprised of 25 footprints per species. XGBoost had an overall accuracy of 91% correct predictions, LDA of 85%.

	Prediction XGBoost			**Prediction LDA**		
Species	***Aonyx cinereus***	***Lutra lutra***	***Lutrogale perspicillata***	***Aonyx cinereus***	***Lutra lutra***	***Lutrogale perspicillata***
Aonyx cinereus	**24**	**0**	**1**	**23**	**2**	**0**
Lutra lutra	**1**	**23**	**1**	**1**	**21**	**3**
Lutrogale perspicillata	**1**	**3**	**21**	**1**	**4**	**20**

Feature importance of the XGBoost and field recommendations

As XGBoost outperformed the LDA approach, we therefore only report the most important features of the better model. For our data, the final XGBoost classifier used 103 variables, with a gain score higher than 0. To take that number of measurements in the field is beyond practicality. Therefore, here we only want to focus on the six most important features, which are illustrated in Figure 5. It is noticeable that these six most essential measurements cover five distances and one triangle, distributed among the whole footprint.

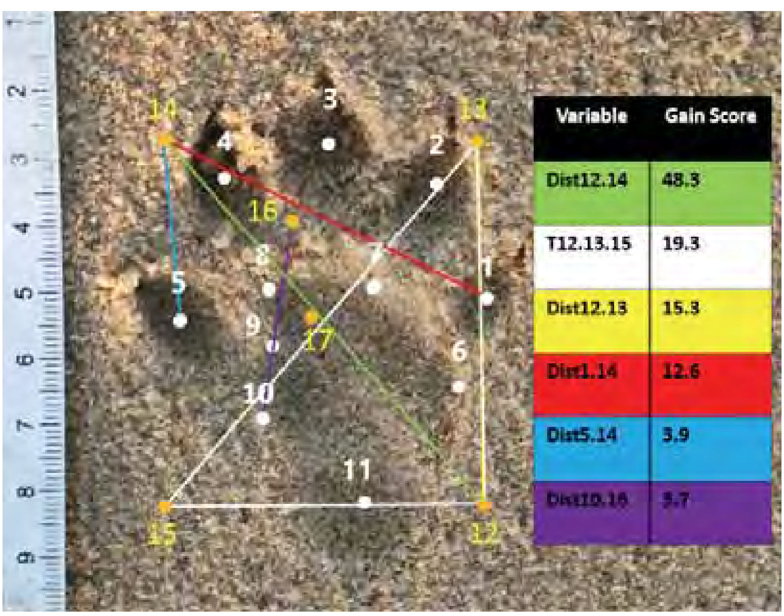

Figure 5. Colour-coded illustration of the six most notable features of the final XGBoost model. The implemented table reports the gain score of the respective variable. The most important feature is distance 12.14, highlighted in green.

Decision tree and potential field identification key

The most influential feature of the model is the distance between point 12 and 14 with a gain score of 48.3. This measurement is equal to the square root of the sum of the squared length and the squared width of the footprint and can be measured in the field.

A further simplified model, a two split regression tree using only this measurement, misclassified 37 of the total 300 footprints, leading to an overall classification accuracy of 88% (Table 4).

Table 4. Confusion matrix of the true species vs. the prediction of a simplified decision tree model with only the variable dist.12.14 and two splits.

	Prediction decision tree model		
Species	***Aonyx cinereus***	***Lutra lutra***	***Lutrogale perspicillata***
Aonyx cinereus	**98**	**2**	**0**
Lutra lutra	**3**	**89**	**8**
Lutrogale perspicillata	**4**	**20**	**76**

Within our dataset, 93% of measurements smaller than 6cm belonged to Asian small-clawed otters. Measurements greater than 8.3 cm belonged to smooth-coated otters in about 90% of the cases. Measurements between 6–8.3cm had the highest probability (~80%) of belonging to Eurasian otters, however, the two other species also had measurements of footprints within this interval (18% smooth-coated otters, 2% Asian small-clawed otters). The full classification tree model with additional information is displayed in Figure 6.

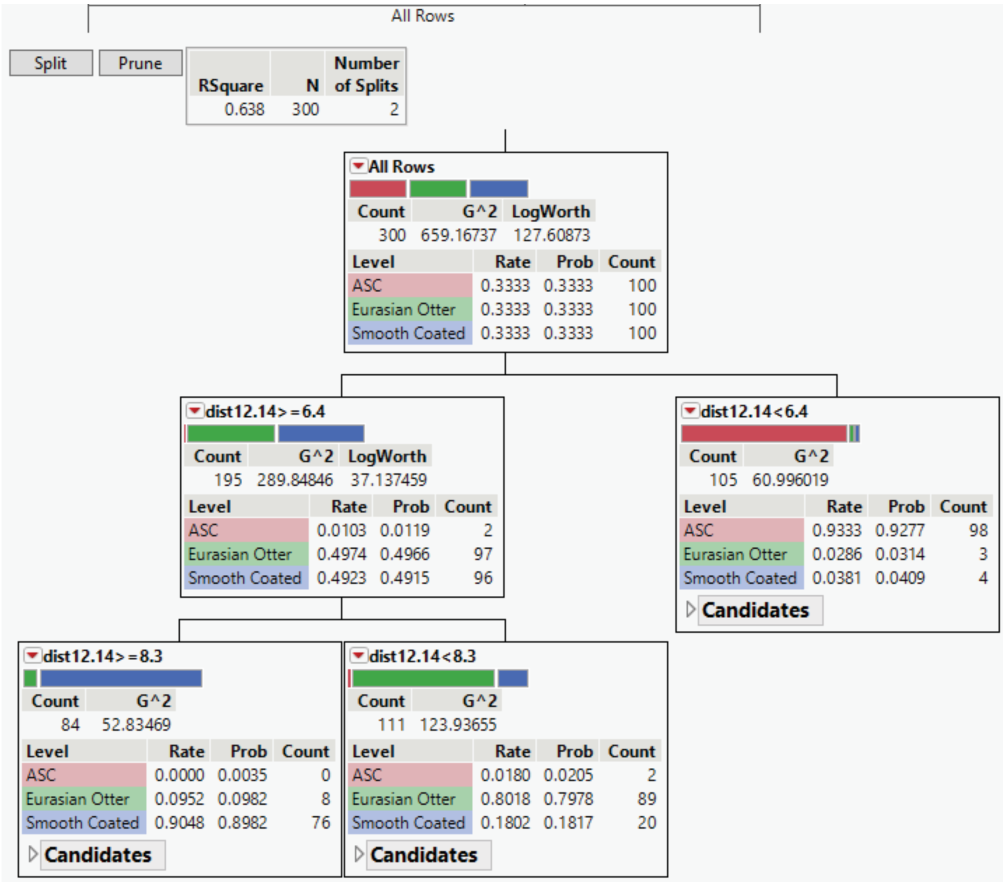

Figure 6. Output of decision tree model on the whole dataset. Target variable was species, explaining variable dist12.14. Only two splits were allowed. The model had an R^2 of 0.638. 88% of the data were classified correctly.

DISCUSSION

This research shows that FIT-models can predict otter species with an excellent accuracy when Machine Learning models trained on a high number of automatically derived morphometrics from otter footprints are applied.

We also show that XGBoost outperformed Linear Discriminant Analysis and therefore recommend the use of XGBoost if a minimal misclassification rate is desired. By investigating the most important features of the best XGBoost model, it was possible to identify a single measurement that can be taken in the field and still enables a good classification accuracy on sight.

These encouraging results confirm that footprints can be a reliable source of species classification for otters. This could be a valuable, cost-effective, non-invasive, and accurate tool for field biologists, conservation policy makers and stakeholders to learn more about otter species distribution on the Asian continent. FIT could therefore be a useful tool for otter surveys by providing data on species distribution and population size in addition to data from camera trapping and spraint analysis.

The lack of accurate data on otter species distribution and the need for otter surveys throughout southeast Asia became evident at the recent Malaysia Otter Workshop 2022, which was held jointly by the Malaysia Otter Network (MON), the Malaysia Nature Society (MNS) and the International Otter Survival Fund (IOSF) in Kuala Selangor Nature Park, Malaysia. The general consensus was that due to habitat loss, pollution and the illegal pet and fur trade, which are both on the rise in southeast Asia, otter numbers are declining **(IOSF Workshop Report, 2022)**. Without accurate data, it is not known how serious the situation for each otter species is, which makes official and accurate surveys all the more important.

To survey more effectively, we need to engage a wider body of data collectors. The engagement of local communities, particularly those still holding Traditional Ecological Knowledge (TEK) could be transformational. Not only would this engage those communities as key stakeholders in the conservation process, but it would greatly augment the quality and volume of data available **(Jewell et al., 2020)**. FIT was inspired by traditional tracking techniques and the data collection protocol is widely accessible. After a short training period, data collection for FIT is straight-forward and only requires a (mobile phone) camera and a metric ruler as equipment.

Even though the results are already encouraging, they could be further improved with several adjustments:

- Increase the size and complexity of the dataset: The results are currently based on a small data set. The aim is to increase this to improve accuracy and test the robustness of the tool.
- In addition to improving the data set size and variation, continued re-training of classification models with clearly identifiable images from local (sub-) populations may be useful. This would likely improve accuracy and enable FIT models to address specific variations in those populations, which will most likely lead to better predictions.
- We would further like to develop models that can also predict sex and individual ID. This has been developed successfully for several other species, such as giant panda (*Ailuropoda melanoleuca*) **(Li et al., 2018),** mountain lion (*Puma concolor*) **(Alibhai et al., 2017)** and Amur tiger (*Panthera tigris altaica*) **(Gu et al., 2014)**. To do so, we require many footprints clearly identifiable to the target class. This is ideally done by collecting footprint images of single, known individuals.
- To have a model that can classify all four Asian otter species, we would like to add footprint images of known hairy-nosed otters (*Lutra sumatrana*) to the database. This has proven challenging so far, as we are aware of only one

captive individual. However, for species classification, we could use good quality field data to develop the necessary algorithm as long as we can be sure that the footprints undoubtedly belong to the species. Long trails from the field, undoubtedly belonging to the same animal, could also be used to train the model for individual ID.

Zoos and field conservationists are therefore invited to contribute footprint images of known Asian otter species and, if possible, known individuals for sex and individual ID. Machine Learning models perform better with more data and otter conservationists are encouraged to further upload any images of known otter species/ individuals following the link and barcode below.

All footprint images will, (given permission) also contribute to WildTrack's AI project (https://www.wildtrack.ml). This project aims to build computer vision models that enable classifications of footprints without the manual setting of landmarks. Once successfully developed, it will enable us to scale up this method significantly. Ultimately, we encourage field researchers to reach out and try this method and cross-validate it with other non-invasive monitoring approaches.

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Disclosure Statement

No potential conflict of interest was reported by the authors.

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REFERENCES

Abu-Rmileh, A, 2019. The multiple faces of 'feature importance' in XGBoost. *Towards Data Science*, 08 February 2019, https://Towardsdatascience.Com/Be-Careful-When-Interpreting-Your-Features-Importance-in-Xgboost-6e16132588e7. Accessed 10 May 2022

Alibhai, SK, Jewell, Z and Law, PR, 2008. A footprint technique to identify white rhino *Ceratotherium simum* at individual and species levels. *Endangered Species Research* 4, 1–2, 205–218.

Alibhai, SK, Jewell, Z and Evans, J, 2017. The challenge of monitoring elusive large carnivores: An accurate and cost-effective tool to identify and sex pumas (*Puma concolor*) from footprints. *PLoS ONE* 12, 3.

Chen, T and Guestrin, C, 2016. XGBoost: A scalable tree boosting system. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 785–794.

Conde, DA, Staerk, J, Colchero, F, da Silva, R, Schöley, J, Baden, HM, Jouvet, L, Fa, JE, Syed, H, Jongejans, E, Meiri, S, Gaillard, J-M, Chamberlain, S, Wilcken, J, Jones, OR, Dahlgren, JP, Steiner, UK, Bland, LM, Gomez-Mestre, I, Lebreton, JD, González Vargas, J, Flesness, N, Canudas-Romo, V, Salguero-Gómez, R, Byers, O, Berg, TB, Scheuerlein, A, Devillard, S, Schigel, DS, Ryder, OA, Possingham, HP, Baudisch, A and Vaupel, JW, 2019. Data gaps and opportunities for comparative and conservation biology. *Proceedings of the National Academy of Sciences of the United States of America*, 19 Apr 2019, 116(19):9658-9664. https://europepmc.org/article/pmc/pmc6511006#free-full-text. Accessed on 12 May 2022.

Duplaix, N and Savage, M, 2018. The global otter conservation strategy. *IUCN/SSC Otter Specialist Group, Salem, Oregon, USA*

Elbroch, M, 2019. *Mammal tracks and signs: a guide to North American species*. Second Edition, Stackpole Books, Guilford, Connecticut.

Evans, JW, Evans, CA, Packard, JM, Calkins, G and Elbroch, M, 2009. Determining observer reliability in counts of river otter tracks. *Journal of Wildlife Management*, *73*,3, 426–432.

Grolms, J, 2021. *Tierspuren Europas: spuren und zeichen bestimmen und interpretieren.* Verlag Eugen Ulmer, Stuttgart.

Gu J, Alibhai SK, Jewell ZC, Jiang G and Ma J, 2014. Sex determination of Amur tigers (*Panthera tigris altaica*) from footprints in snow. *Wildlife Society Bulletin 04/2014*, 38, 3, 495–502.

IOSF Malaysian Workshop Report ,**2022.** *Otter, Journal of the International Otter Survival Fund*. Current issue.

Jewell, Z, 2013. Effect of monitoring technique on quality of conservation science. *Conservation Biology*, *27*, 3, 501–508.

Jewell, ZC, Alibhai, SK, Weise, F, Munro, S, van Vuuren, M and van Vuuren, R, 2016. Spotting cheetahs: identifying individuals by their footprints. *Journal of Visualized Experiments*, 111, 1–11.

Jewell, ZC, Alibhai, S, Law, PR, Uiseb, K and Lee, S, 2020. Monitoring rhinoceroses in Namibia's private custodianship properties. *Peer Journal* 8:e9670.

Li, BV, Alibhai, S, Jewell, Z, Li, D, and Zhang, H, 2018. Using footprints to identify and sex giant pandas. *Biological Conservation*, 218, 83–90.

Liebenberg, L, 2021. The origin of science: the evolutionary roots of scientific reasoning and its implications for tracking science. *Cape Town, South Africa: CyberTracker*.

Petso, T, Jamisola, RS and Mpoeleng, D, 2022. Review on methods used for wildlife species and individual identification. *European Journal of Wildlife Research*, 68, 1, 1–18.

Ramos, SC, Shenk, TM and Leong, KM, 2016. Introduction to traditional ecological knowledge in wildlife conservation. *Natural Resource Report NPS/NRSS/BRD/NRR—2016/1291*. National Park Service, Fort Collins, Colorado.

Rhyder, J, 2021. *Tracks and signs: a guide to the field signs of mammals and birds of the U.K.* The History Press, Cheltenham, Gloucestershire.

Sharma, S, Jhala, Y and Sawarkar, VB, 2005. Identification of individual tigers (*Panthera tigris*) from their pugmarks. *Journal of Zoology* 267, 1, 9-18.

Vieira, MAR, von Muhlen, EM and Shepard, GH Jr., 2015. Participatory monitoring and management of subsistence hunting in the Piagaçu-Purus Reserve, Brazil, *Conservation and Society*, 13, 3, 254-264.

Wolfinger, R, 2020. XGBoost Add-In for JMP Pro, *JMP User Community blog on topic of JMP Add-Ins*, 28 April 2022, https://community.jmp.com/t5/JMP-Add-Ins/XGBoost-Add-In-for-JMP-Pro/ta-p/319383. Accessed 01 June 2022.

Yoxon, P and Yoxon, GM, 2017. *Otters of the World*. Whittles Publishing Ltd, Dunbeath, Caithness, Scotland.

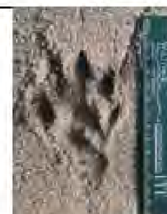
Appendix

FIT Zoo Protocol for Otter

You need:

- sand, rake, trowel or similar
- metric(!) ruler (an L-shaped ruler/tri-square is ideal)
- label
- smartphone camera/digital camera
- watering can if necessary

Sand patches should be strategically placed at frequently used areas, e.g. the entrance of nest boxes, near feeding places, at water entry points or at the otters' patrol routes along fence lines.

1.	**Prepare** the ~1cm deep sand patch by raking and levelling with trowel, add some water with watering can first if sand too dry. The sand should be level but not too compressed in the end.	
2.	Let **one individual walk across** the sand patch so that you know for sure which otter left the footprints.	
3.	- Take **overhead image of the trail*** (several tracks) - Locate complete **left front (LF) footprints** (see image on right) for FIT and circle them. - Any other good quality footprints of the **other feet** (RF, LH, RH) can be used for WildTrack's AI project.	
4.	Place a **metric(!) L-shaped ruler** approximately **2cm above the footprint**, framing the track as shown in the image on the right (and making sure not to touch the edges of the footprint).	
5.	Add a **label** stating the date and place of where the footprint was taken. Also note the number or name of the animal and the name of the photographer. When following a trail*, number it and mark the tracks* with letters 'A', 'B', 'C' etc. Also give foot ID as LF (left front) (or RF, LH, RH if you are also collecting for AI project)	**DATE:** 04 April 2019 **ANIMAL ID:** AJU05/name **LOCATION:** name of zoo______ **FOOTPRINT #:** 1 A, B, C______ **FOOT ID:** LH (left hind)______ **PHOTOGRAPHER:** LS______
6.	Take a **close-up photo** of the footprint, incl. the label and enough of the ruler to clearly see a measurement of at least 5cm. It is important that the camera is absolutely parallel to the footprint (ensure right angle of ruler compliments right angle of camera screen). Photos of completely shaded footprints normally give the clearest image. Use an umbrella or similar to create shade if necessary.	

***track** = a footprint; **trail** = unbroken line of tracks belonging to one individual