

# Computer vision model for the detection of canine pododermatitis and neoplasia of the paw

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## Abstract

**Background:** Artificial intelligence (AI) has been used successfully in human dermatology. AI utilises convolutional neural networks (CNN) to accomplish tasks such as image classification, object detection and segmentation, facilitating early diagnosis. Computer vision (CV), a field of AI, has shown great results in detecting signs of human skin diseases. Canine paw skin diseases are a common problem in general veterinary practice, and computer vision tools could facilitate the detection and monitoring of disease processes. Currently, no such tool is available in veterinary dermatology.

**Animals:** Digital images of paws from healthy dogs and paws with pododermatitis or neoplasia were used.

**Objectives:** We tested the novel object detection model Pawgnosis, a Tiny YOLOv4 image analysis model deployed on a microcomputer with a camera for the rapid detection of canine pododermatitis and neoplasia.

**Materials and Methods:** The prediction performance metrics used to evaluate the models included mean average precision (mAP), precision, recall, average precision (AP) for accuracy and frames per second (FPS) for speed.

**Results:** A large dataset labelled by a single individual (Dataset A) used to train a Tiny YOLOv4 model provided the best results with a mean mAP of 0.95, precision of 0.86, recall of 0.93 and 20 FPS.

**Conclusions and Clinical Relevance:** This novel object detection model has the potential for application in the field of veterinary dermatology.

## KEY WORDS

artificial intelligence, deep learning, dermatology, machine learning, telemedicine, tiny YOLO

## INTRODUCTION

Artificial intelligence (AI) can provide valuable tools for veterinary medicine to alleviate diagnosis difficulties and long-term disease management problems, similar to their applications in human medicine. Computer vision (CV) is a field of AI that enables computers to derive meaningful predictions of various aspects of diseases, by interpreting digital images, videos and other visual sources.<sup>1,2</sup> In human dermatology, CV approaches to detecting signs of skin diseases have been demonstrated to perform equally to those of board-certified specialists.<sup>3</sup> Object detection is a CV approach

and is the process of identifying and locating specific objects in images or videos using CV algorithms. It can facilitate a fast, noninvasive diagnosis, that does not require additional staff or manual labour. Diagnostic support for skin lesions or disease detection would be a significant asset to veterinarians worldwide.

Convolutional neural networks (CNN) are types of neural networks frequently utilised for medical image analysis.<sup>4</sup> These networks can accomplish tasks such as image classification, object detection and segmentation (see Appendix S1). Large datasets of thousands to millions of images have been utilised to train CNN models to classify and detect a wide array of objects.<sup>5,6</sup>

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One limiting factor for creating such models is obtaining a sufficiently large and comprehensive dataset to train a CNN structure. The use of transfer learning, a method in which pre-existing models are pre-trained on extensive image datasets, represents a feasible approach for training CV models for detection of signs of disease.<sup>5</sup> After transfer learning, the CV models can be tailored to the specific task of interest.<sup>6</sup> In machine learning and CV, object detection models analyse an image and identify the presence of specified object classes within it. Upon detection, bounding boxes demarcate these objects. The model identifies the class by shape, colour and texture, differentiating from the background and calculates a class probability.<sup>7</sup>

You Only Look Once (YOLO) is a CNN for performing real-time object detection deep learning that has become a standard method in the field of CV.<sup>8</sup> The first version of YOLO was released in 2015.<sup>8</sup> YOLOv4 is an architecture originally implemented in a TensorFlow framework detecting objects in one step.<sup>9</sup> Tiny YOLOv4 is a compressed version of YOLOv4 designed for smaller devices with limited computing power.<sup>10</sup> Tiny YOLOv4 models have a simpler network structure and fewer parameters to train compared to YOLOv4.<sup>11</sup> Higher speed is traded-off to lower accuracy by Tiny YOLOv4 compared to YOLOv4.<sup>9,12–14</sup>

The paws are a discreet body region with well-recognised disease conditions for exploring the application of object detection, particularly for research purposes. One of the most common diseases is canine pododermatitis.<sup>15</sup> This study aimed to train and deploy a CV pododermatitis model named Pawgnosis, which can detect healthy dog paws, pododermatitis and neoplasia cases based on images, videos or live camera capture in real-time.

## MATERIALS AND METHODS

### Image collection and definition of classes

Still and video images of dog paws were obtained during the course of clinical dermatological practice at the University of Wisconsin-Madison School of Veterinary Medicine. Clients provided written informed consent for image acquisition. The criteria for image collection included being healthy, having pododermatitis or showing signs of neoplasia. Images used in this study were obtained from ventral, dorsal and lateral positions of the dogs' paws, with various backgrounds and lighting. Images were taken with the interdigital spaces open (viewing the webs) and closed, as well as of the palmar/plantar aspects between the paw pads.

The three object classes used in this study are defined as follows. Healthy paws were canine paws free from any clinically observable disease with no signs of inflammation, abrasions or masses. Pododermatitis paws were defined as canine paws exhibiting clinical signs of inflammation resulting from any underlying diseases without signs of neoplasia. Signs of inflammation on the paws included single or multiple lesions that were dry or crusted, oedematous, erythematous,

nodular, ulcerated or exudative and could include focal areas of alopecia. Neoplasia paws were defined as canine paws that had a mass and, after additional diagnostic testing, were diagnosed as squamous cell carcinoma, melanoma, osteosarcoma, mast cell tumours or malignant soft tissue sarcomas. Lymphoma cases were not included owing to a lack of images.

### Image labelling and definition of datasets

After collection, the images were manually labelled using the three previously defined classes (Healthy, Pododermatitis, Neoplasia) for object detection and the program, LABELIMG.<sup>16</sup> YOLO-formatted bounding boxes and annotation files were created for each image of the paws for each of the three classes. These boxes were then labelled as 'healthy', 'pododermatitis' or 'neoplasia'.

Three different datasets were generated to compare the predictive performances of the resulting object detection models. Mean average precision (mAP), precision and recall metrics for all classes and average precision (AP) for each class were computed.<sup>17</sup> For each model, the inference time to predict bounding boxes and corresponding class labels in an image was measured using frames per second (FPS). Dataset A contained 575 images labelled by one person drawing relatively wide boxes around the entire paw area during labelling (Table S1). Dataset B contained the same 575 images labelled by three people (Table S1). Labelling was divided equally with a mix of narrow boxes around lesions or wide boxes around the area of the affected paws during labelling resulting in multiple boxes per image. Dataset C included 301 images labelled by two people drawing a mix of relatively narrow boxes around the affected paw area, resulting in multiple nonoverlapping bounding boxes or wide boxes around the area of the affected paw (Table S1).

### Model building

All data processing and model training were performed in PYTHON 3.8.<sup>18</sup>

The three datasets were split at random into 90% train and 10% validation image sets without data leakage, where images of the same paw are deleted and are not part of the train and validation datasets simultaneously. The frequencies of the three class labels per dataset (A, B and C) can be found in Table S2.

For the purpose of transfer learning, the Tiny YOLOv4 model was initialised using classification weights pre-trained on ImageNet.<sup>19</sup> Models were trained using an input size of  $416 \times 416$  pixels for a maximum number of batches of 6000 with a batch size of 64 and a learning rate of 0.00261. The models were trained in triplicates for each dataset (A, B and C) and prediction performance metrics were averaged over the three training runs.

The weights of the best model over the three training runs of Dataset A were used for deployment of

the Tiny YOLOv4 model on an edge device. Using the same training and validation datasets from the best of three Tiny YOLOv4 training runs, 5s and Tiny YOLOv7 models were trained. The YOLOv5 (<https://zenodo.org/record/7347926>) and YOLOv7<sup>20</sup> implementations<sup>20</sup> are based on Pytorch (Linux Foundation),<sup>21</sup> and were used as a comparison for speed of detections on an edge device. The edge device used for deployment of the Tiny YOLOv4, YOLOv5s and Tiny YOLOv7 models was a Jetson Xavier NX ([www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetson-xavier-nx/](http://www.nvidia.com/en-us/autonomous-machines/embedded-systems/jetson-xavier-nx/)) connected to an OAK-1 camera (Luxonis) that applies the DepthAI framework for inference.<sup>22</sup> This set-up of the edge device prototype was independent from web access and battery-powered for eight hours of continuous detection. For deployment of the Tiny YOLOv4 model in our veterinary dermatology clinic, a Colab notebook (Google)<sup>23</sup> was adapted to run a real-time built-in detection camera on a smartphone. This deployment required web access and a free Google Colab account.

## RESULTS

The results of the model training sessions and prediction performances during deployment of the resulting models are summarised below.

The training duration for each model was under two hours. The mAP values for all three datasets were stable after an iteration number of approximately 3000.

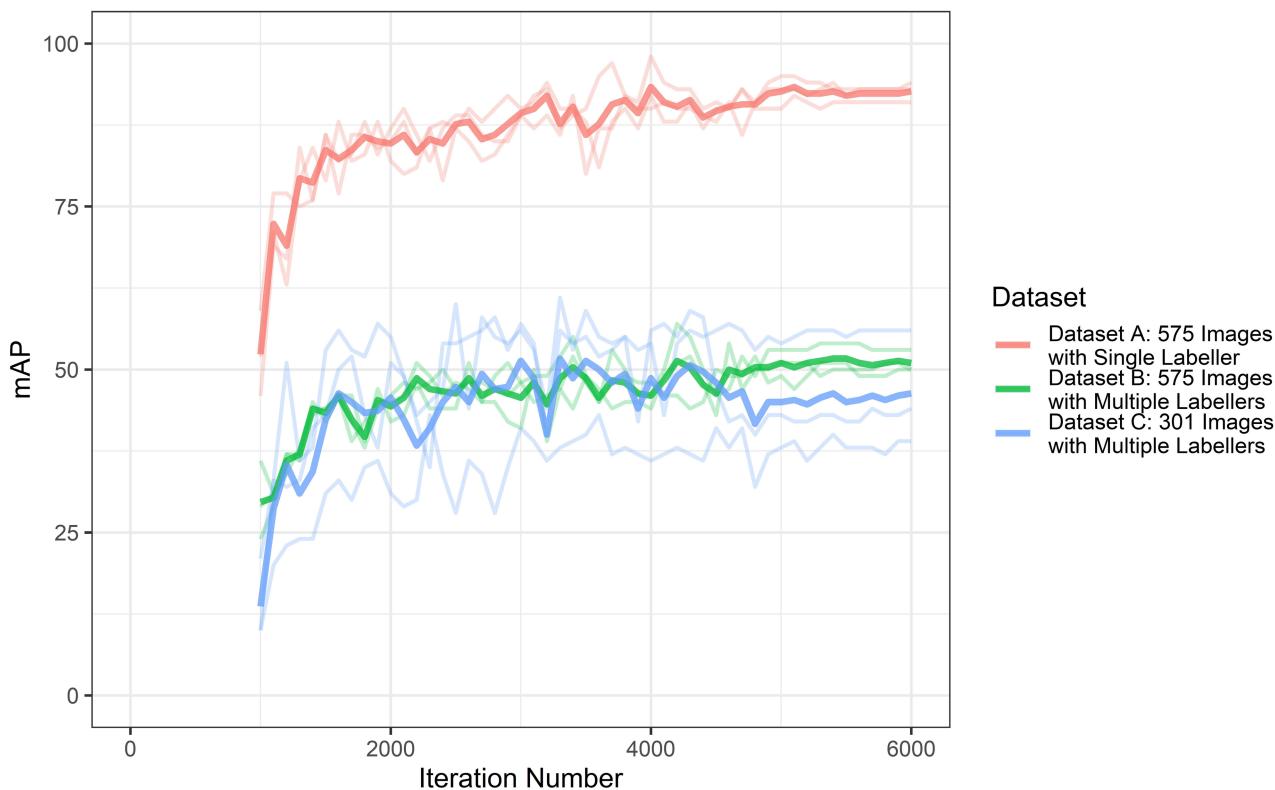
The mAP for Dataset A was higher than for both datasets B and C (Figure 1).

The mAP and recall for Dataset A were higher than for both Dataset B and C, while the precision was similar for all three datasets (Figure 2). The numeric values for means and standard errors (SEs) of the mAP metrics can be found in Table S2.

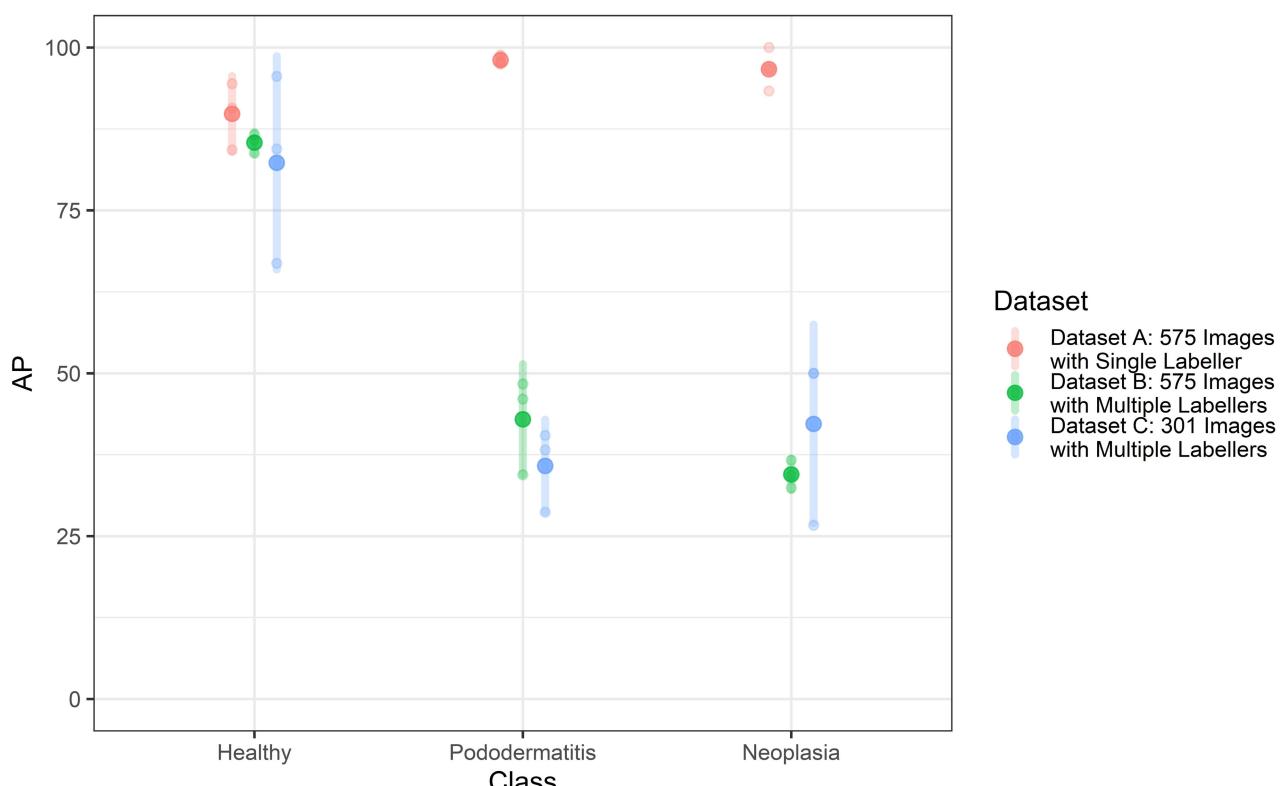
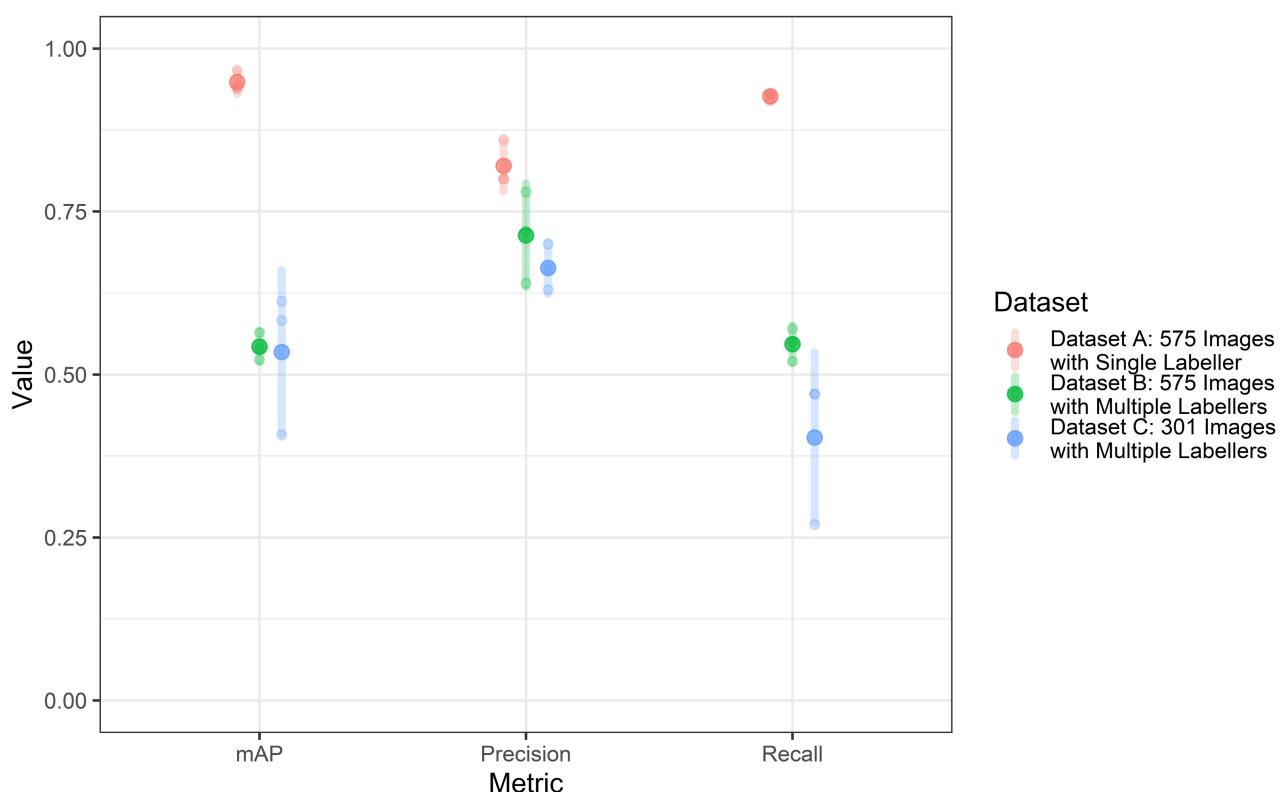
The AP of pododermatitis and neoplasia for Dataset A was higher than those for both datasets B and C, while the AP of healthy was similar for all three datasets (Figure 3). The numeric values for means and SEs of the AP metrics can be found in Table S3.

Figure 4 shows typical images for the three classes, Healthy, Pododermatitis and Neoplasia and their detections using bounding boxes with class probabilities for each of the three datasets (A, B and C). Detections of the three classes from Dataset A (Figure 4a–c) show larger bounding boxes and higher class probabilities compared to those for datasets B and C. No detections resulted from Dataset C for the healthy and neoplasia classes (Figure 4g,i, respectively). The smaller bounding boxes from datasets B and C were occasionally drawn outside the relevant paw area in the images from Pododermatitis (Figure 4e,h).

The performance metrics for Tiny YOLOv4, YOLOv5s and Tiny YOLOv7 models trained on Dataset A are summarised in Table 1. Tiny YOLOv7 had the highest mAP (0.973) compared to the other two models. We deployed these models on an edge device, where Tiny YOLOv7 was the fastest with 40 FPS, and Tiny YOLOv4 and YOLOv5s had 20 FPS.



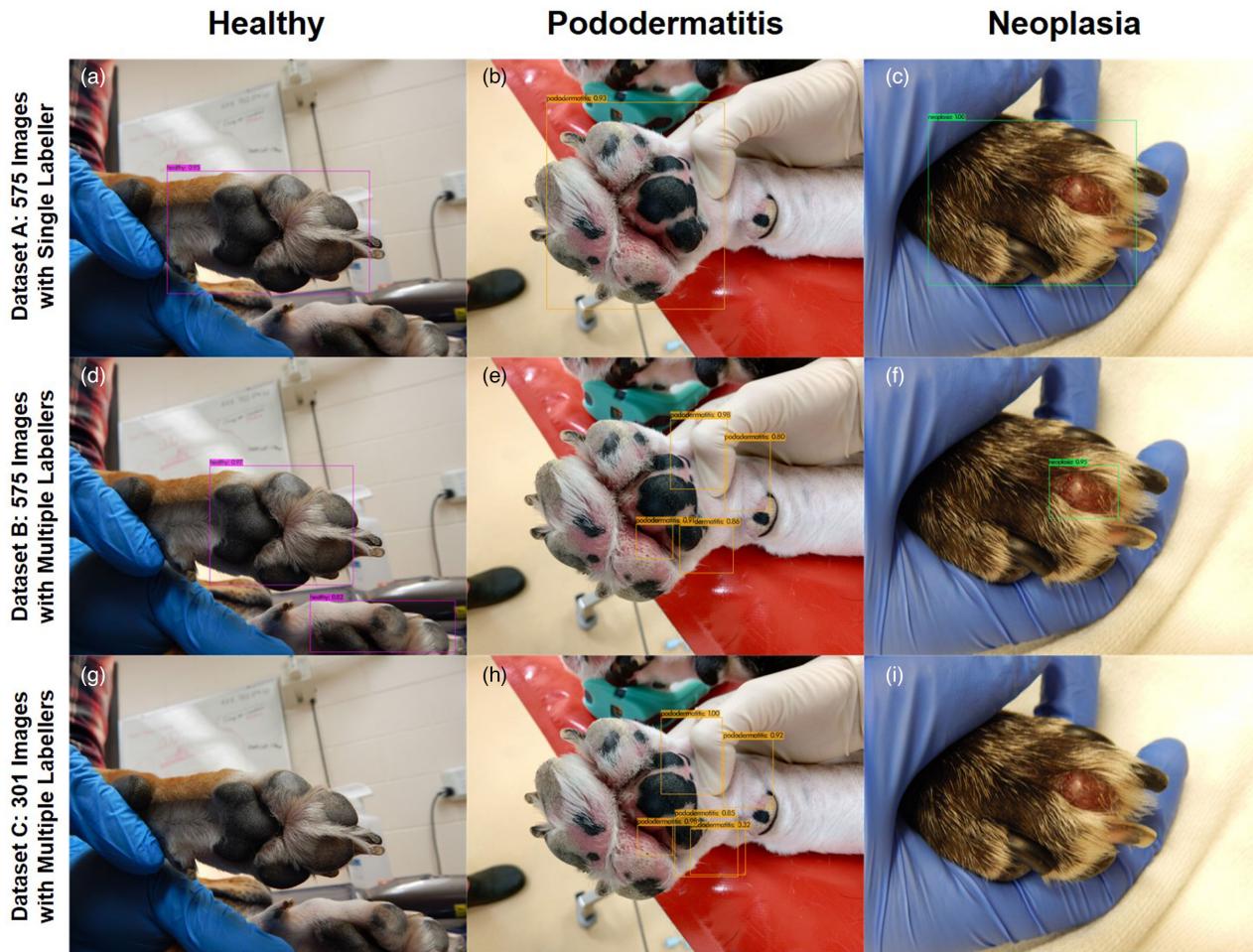
**FIGURE 1** Mean average precision (mAP) over iteration number for training Tiny YOLOv4 custom models. Plots are grouped by training dataset where the thin, transparent lines correspond to three different training sessions per dataset and the thick, opaque line corresponds to the means of mAP from the three training sessions per dataset (colours: red, Dataset A; green, B; blue, C).



**FIGURE 2** Mean and 95% confidence intervals for three performance metrics of each of the three datasets using Tiny YOLOv4. Plots are grouped by mean average precision (mAP), precision and recall for each dataset. Small circles correspond to distinct training runs, large circles correspond to group means, and the vertical lines correspond to the 95% confidence interval (colours: red, Dataset A; green, B; blue, C).

We conducted a preliminary limited deployment of the Tiny YOLOv4 model in our dermatological exam room as illustrated in Figure 5. Figure 5a shows the

Jetson Xavier NX single-board computer connected to the OAK-1 camera for the real-time detection of the three classes: Healthy, Pododermatitis and



**FIGURE 4** Image matrix of predictions from typical images of the Healthy, Pododermatitis and Neoplasia classes using the best Tiny YOLOv4 model with the highest average mean average precision (mAP) value from the three training runs (top row: Dataset A; middle row: B; bottom row: C). Matrix rows correspond to the training dataset and columns represent classes Healthy (magenta boxes), Pododermatitis (orange boxes) and Neoplasia (green boxes). The predictions are displayed using a bounding box and class label with corresponding prediction probability.

**TABLE 1** Mean and standard error (SE) of mean average precision (mAP), precision and recall for Tiny YOLOv4, YOLOv5s and Tiny YOLOv7 models trained on Dataset A.

Model	Precision	Recall	mAP	Average precision		
				Healthy	Pododermatitis	Neoplasia
Tiny YOLOv4	0.86	0.93	0.967	94.4	98.9	96.7
YOLOv5s	0.953	0.93	0.971	92.9	98.9	99.5
Tiny YOLOv7	0.912	0.96	0.973	96.3	99.5	96.2

Neoplasia. [Figure 5b](#) shows the resulting bounding box, class label and class prediction probability during real-time detection of a pododermatitis lesion on a dog's paw, and [Figure 5c](#) shows the schematic set-up of the edge device used for deployment in the clinical setting.

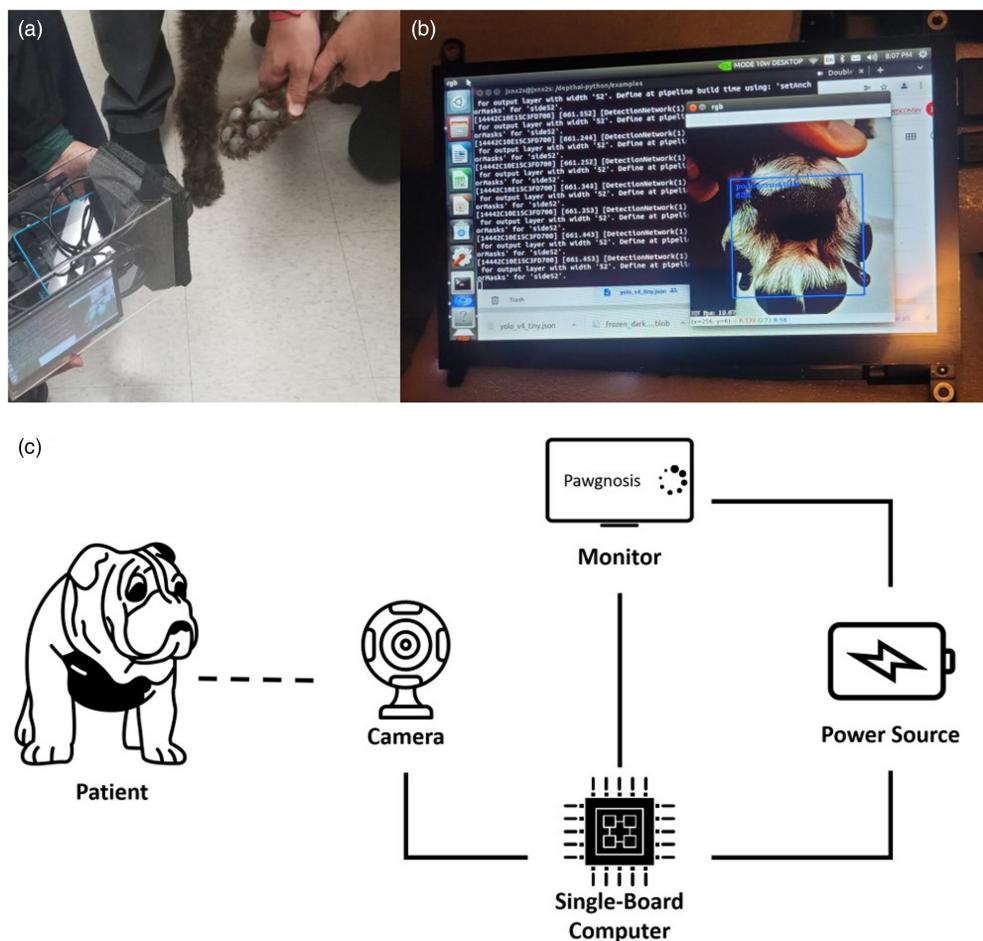
## DISCUSSION

In this study, we applied CNNs to detect and classify objects in images in real-time. The Pawgnosis model predicted whether a canine paw showed characteristics of pododermatitis or neoplasia, or was clinically normal, with high performance after learning from a limited number of images. We demonstrated that the

Pawgnosis tool can detect the three classes with supervision in a veterinary clinical setting.

Models constrained to these three classes are not without limitations, and the applications of such models could be expanded by subdividing and increasing the number of these classes. The model could be broadened to detect early flares of pododermatitis resulting from atopic dermatitis (AD). Further studies may be performed to show agreement between the model detections and the validated AD scoring system Canine Atopic Dermatitis Extent and Severity Index (CADESI)-04,<sup>24</sup> or other scores.

The differences in model performance between the three datasets A, B and C emphasise the importance of sample size and consistent labelling techniques for achieving optimised prediction performance of CV models.



**FIGURE 5** (a) Portable, battery-powered Jetson Xavier NX single-board computer connected to a Luxonis OAK-1 camera detecting three classes Healthy, Pododermatitis and Neoplasia in a clinical setting. (b) Canine pododermatitis detection box with class label and class probability. (c) Schematic set-up for single-board computer, camera, LED monitor and power source.

The model returned higher mean mAP when trained on Dataset B (575 images with multiple labellers) compared to training on Dataset C (301 images with multiple labellers). When comparing a single labeller (Dataset A) to multiple labellers (Dataset B and C), the model returned higher mean mAP values when trained on Dataset A than when trained on datasets B and C (Figure 1). This holds true across all other performance metrics including precision and recall (Figure 2). A single labeller achieved a better performance than multiple person labelling. Dataset A outperformed datasets B and C for mAP (0.95 compared to 0.54 and 0.53, respectively), recall (0.93 compared to 0.55 and 0.40, respectively) and precision (0.82 compared to 0.71 and 0.66, respectively).

The AP of Dataset A was higher than the mAPs of datasets B and C for both the pododermatitis and neoplasia classes, while the difference in AP between Dataset A and the other two datasets was reduced for the healthy class (Figure 3). This suggests that labelling disproportionately affected paws with dermatological lesions compared to healthy paws. Healthy paws were generally labelled with a single box around the entire paw across all datasets. Therefore, more boxes with fewer general features would result in lower accuracy.

The proportion of the performance for Dataset A attributed to a single labeller or an increase in size and simplicity of labelled boxes is unknown. We assume that the benefits of a single labeller contributed to a

reduction of inter-labeller variation, resulting in improved labelling consistency within the dataset. An increase in size of the labelled boxes to include the whole paw also decreased the inter-labeller variation. Consistent labelling of the whole paw in Dataset A was more accurate than labelling of individual lesions in datasets B and C. Further studies comparing datasets with the same labelling criteria and different number of labellers to datasets with different labelling criteria and the same number of labellers can be performed to determine the true relative contribution for each factor. For the current analysis, an increased labelling consistency and increased sample size of datasets increased the performance of object detection CV models for dermatological lesions. Labelling under the supervision of board-certified veterinary dermatologists is strongly recommended.

Artificial intelligence in veterinary medicine is an emerging field that has mostly been applied to large animals, clinical and anatomical pathology and radiology.<sup>25–36</sup> The use of AI for skin disease diagnosis in dogs is rare.<sup>37–39</sup> Previous studies used image classification to label entire images, while the current approach uses object detection to not only locate, but also label individual objects within an image. A study reported a YOLOv5 model for dry eye disease in dogs with a very high mAP of 0.995.<sup>40</sup> Another group built a model for dermatophytosis, mange and fleas.<sup>38</sup> Another model evaluated 12 dog skin diseases.<sup>37</sup> In 2022, researchers evaluated

images from dogs with fungal skin infection, bacterial dermatitis and allergies.<sup>39</sup> No further details are provided regarding how the diagnoses were made. From a dermatological perspective, it also was unknown if the dogs had secondary skin infections and what the most common complicating factors were. Limited information was provided by all three studies regarding the individuals that made the diagnosis and their knowledge and training in veterinary dermatological practice. Overall, these previous studies as well as the current study provide the first steps and serve as a launch pad for the implementation of AI in veterinary dermatology.

Only YOLO models were implemented to compare the performance of the three labelled datasets and embedded on an edge device to detect the three classes in a clinical setting. Further studies can explore the differences between the three state-of-the-art YOLO models and other object detection models. Two-stage object detection models such as Faster R-CNNs and Cascade R-CNNs<sup>41,42</sup> can increase accuracy for improved prediction on a stand-alone device.<sup>41,42</sup> Other one-stage object detection models such as SSD and SSD Lite<sup>41,42</sup> can be lightweight and increase speed for improved prediction on a mobile platform.<sup>41,42</sup> However, YOLO models provided higher speed and similar mAP compared to SSD, ResNet and other models in human dermatological practice.<sup>43,44</sup>

Our next goal is to deploy the YOLO model on an edge device in a clinical setting for external validation. CV can be deployed on a laptop or desktop, an edge device or a smartphone cloud-based application. Depending on the purpose of each model, a different option can be deployed. These models can be used for teaching both veterinary students and veterinarians and aiding in diagnostic decision-making.

## CONCLUSION

To the best of the authors' knowledge, the Pawgnosis tool is the first object detection model using CV in veterinary dermatology. It has the potential to become an accurate and fast CV model for the management of canine pododermatitis. The model can be further improved for real-time detection of pododermatitis and monitoring of progression or treatment effects. It also can make recommendations for future diagnostic steps. Implementing Pawgnosis on portable devices with first opinion veterinary practitioners will further optimise the model. Pawgnosis may be used as a clinical, research or didactic tool. Further studies are needed to expand its abilities and validate its generalisability and applicability in everyday clinical practice.

## AUTHOR CONTRIBUTIONS

**Andrew Smith:** Formal analysis; investigation; methodology; writing – original draft. **Patrick W. Carroll:** Formal analysis; methodology; writing – original draft; investigation. **Srikanth Aravamuthan:** Formal analysis; investigation; methodology; software; visualization; writing – review and editing. **Emil Waller:** Formal analysis; methodology; investigation; software. **Haley Lin:** Formal analysis; investigation;

writing – original draft. **Kelly Anklam:** Investigation; writing – review and editing. **Dörte Döpfer:** Conceptualization; formal analysis; investigation; methodology; data curation; project administration; software; writing – review and editing; supervision.

**Neoklis Apostolopoulos:** Conceptualization; formal analysis; investigation; methodology; data curation; project administration; supervision; writing – review and editing; software; validation; writing – original draft.

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## CONFLICT OF INTEREST STATEMENT

None declared.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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## 摘要

**背景:** 人工智能已成功应用于人类皮肤科。人工智能利用卷积神经网络(CNN)完成图像分类、对象检测和分割等任务，促进早期诊断。计算机视觉(CV)是人工智能的一个领域，在检测人类皮肤疾病迹象方面取得了巨大成果。犬爪部皮肤病是普通兽医临床中的一个常见问题，计算机视觉工具可以促进疾病过程的检测和监测。目前，兽医皮肤科还没有这种工具。

**动物:** 使用健康犬的爪子和患有爪部皮炎或肿瘤的爪子的数字图像。

**目的:** 我们测试了新型物体检测模型Pawgnosis，这是一种部署在带摄像头的微型计算机上的Tiny YOLOv4图像分析模型，用于快速检测犬爪部皮炎和肿瘤。

**材料和方法:** 用于评估模型的预测性能指标包括平均精度(mAP)、精度、召回率、精度的平均精度(AP)和速度的每秒帧数(FPS)。

**结果:** 用于训练Tiny YOLOv4模型的由单个个体标记的大型数据集(数据集A)提供了最佳结果，平均mAP为0.95，精度为0.86，召回率为0.93和20 FPS。

**结论和临床相关性:** 这种新的目标检测模型在兽医皮肤科领域具有应用潜力。

## Zusammenfassung

**Hintergrund:** Die künstliche Intelligenz (KI) wurde in der Humandermatologie bereits erfolgreich eingesetzt. Die KI nutzt konvolutionale neurale Netzwerke (CNN), um Aufgaben wie Klassifizierung von Bildern, Objekterkennung und Einteilung zu erfüllen und eine frühe Diagnose zu ermöglichen. Computer Vision (CV), ein Bestandteil der KI, hat bei der Erkennung von Hautkrankheiten beim Menschen großartige Ergebnisse gebracht. Hauterkrankungen der Pfoten des Hundes sind ein häufiges Problem in der allgemeinen veterinärmedizinischen Praxis, wobei Computervisionsinstrumente die Erkennung und das Monitoring des Krankheitsverlaufs ermöglichen könnten. Zurzeit gibt es noch keine derartigen Instrumente in der Veterinärdermatologie.

**Tiere:** Digitale Bilder der Pfoten von gesunden Hunden und Pfoten mit Pododermatitis oder Neoplasie wurden verwendet.

**Ziele:** Wir haben das neue Objekt-Detektionsmodell Pawdiagnosis getestet, ein Tiny YOLOv4 Bildanalyse Modell, welches auf einem Mikrocomputer mit einer Kamera zur Schnellentdeckung von caniner Pododermatitis und Neoplasie eingerichtet war.

**Materialien und Methoden:** Die metrischen Daten zur Vorhersage der Leistungsfähigkeit, die eingesetzt wurden, um die Modelle zu evaluieren, bestanden aus durchschnittlicher Durchschnittspräzision (mAP), Präzision, Abrufbarkeit, Durchschnittspräzision (AP) und Rahmen pro Sekunde (FPS) für die Geschwindigkeit.

**Ergebnisse:** Ein großer Datensatz eines einzigen Individuums (Dataset A), welches verwendet wurde, um ein Tiny YOLOv4 Modell zu trainieren, ergab die besten Ergebnisse mit einem durchschnittlichen mAP von 0,95, Präzision von 0,86, Abrufbarkeit von 0,93 und 20 FPS.

**Schlussfolgerungen und klinische Bedeutung:** Dieses neue Objekterkennungsmodell hat das Potential für den Einsatz im Bereich der Veterinärdermatologie.

## 要約

**背景:** 人工知能(AI)はヒトの皮膚科学にうまく利用されている。AIは、畳み込みニューラルネットワーク(CNN)を利用して、画像分類、物体検出、セグメンテーションなどのタスクを達成し、早期診断を容易にしている。AIの一分野であるコンピュータ・ビジョン(CV)は、人間の皮膚病の兆候を検出するのに大きな成果を示している。イヌの肉球皮膚疾患は、一般的な獣医診療においてよく見られる問題であり、コンピュータビジョントールを用いることで、疾患プロセスの検出やモニタリングが容易になる可能性がある。現在のところ、獣医皮膚科学ではこのようなツールは利用できない。

**動物:** 健常犬の肉球のデジタル画像および足底皮膚炎や腫瘍のある肉球のデジタル画像を使用した。

**目的:** 我々は、犬の足底皮膚炎および腫瘍の迅速な検出のために、カメラ付きマイクロコンピュータ上に配置されたTiny YOLOv4画像解析モデルである新しい物体検出モデルPawgnosisをテストした。

**材料と方法:** モデルの評価に使用した予測性能指標は、mean average precision(mAP)、適合性、再現性、平均適合率(AP)、フレームレート(FPS)である。

**結果:** 1個人によってラベル付けされた大規模データセット(データセットA)は、Tiny YOLOv4モデルの訓練に使用され、平均mAP 0.95、適合性0.86、再現性0.93、FPS 20という最高の結果を示した。結論と臨床的妥当性 この新しい物体検出モデルは、獣医皮膚科学の分野で応用できる可能性がある。

## Resumo

**Contexto:** A inteligência artificial (IA) tem sido utilizada com sucesso na dermatologia humana. A IA utiliza redes neurais convolucionais (CNN) para realizar tarefas como classificação de imagens, detecção e segmentação de objetos, facilitando o diagnóstico precoce. A visão computacional (VC), um campo da IA, tem mostrado ótimos resultados na detecção de sinais de doenças de pele humana. As doenças de pele das patas caninas são um problema comum na prática veterinária geral, e as ferramentas de visão computacional podem facilitar a detecção e monitoramento dos processos patológicos. Atualmente, tal ferramenta não está disponível em dermatologia veterinária.

**Animais:** Foram utilizadas imagens digitais de patas de cães saudáveis e de patas com pododermatite ou neoplasia.

**Objetivos:** Testamos o novo modelo de detecção de objetos *Pawgnosis*, um modelo de análise de imagem *Tiny YOLOv4* implantado em um microcomputador com câmera para a detecção rápida de pododermatite e neoplasia canina.

**Materiais e Métodos:** As métricas de previsão de performance utilizadas para avaliar os modelos incluíram precisão média (mAP), precisão, repetibilidade, precisão média (AP) para acurácia e quadros por segundo (FPS) para velocidade.

**Resultados:** Um grande banco de dados identificado por um único indivíduo (*Dataset A*) usado para treinar um modelo *Tiny YOLOv4* forneceu os melhores resultados com uma mAP média de 0,95, precisão de 0,86, repetibilidade de 0,93 e 20 FPS.

**Conclusões e relevância clínica:** Este novo modelo de detecção de objetos tem potencial para aplicação no campo da dermatologia veterinária.

## RESUMEN

**Introducción:** La inteligencia artificial (AI) se ha utilizado con éxito en dermatología humana. La AI utiliza redes neuronales convolucionales (CNN) para realizar tareas como clasificación de imágenes, detección y segmentación de objetos, lo que facilita el diagnóstico temprano. La visión computerizada (CV), un campo de la AI, ha mostrado excelentes resultados en la detección de signos de enfermedades de la piel humana. Las enfermedades de la piel de las extremidades caninas son un problema común en la práctica veterinaria general, y las herramientas de visión computerizada podrían facilitar la detección y el seguimiento de los procesos patológicos. Actualmente, no existe ninguna herramienta de este tipo disponible en dermatología veterinaria.

**Animales:** Se utilizaron imágenes digitales de extremidades de perros sanos y extremidades con pododermatitis o neoplasia.

**Objetivos:** probamos el novedoso modelo de detección de objetos Pawgnosis, un modelo de análisis de imágenes Tiny YOLOv4 implementado en una microcomputadora con una cámara para la detección rápida de pododermatitis y neoplasias caninas.

**Materiales y métodos:** Las valoraciones de rendimiento de predicción utilizadas para evaluar los modelos incluyeron precisión promedio media (mAP), precisión recuperada, precisión promedio para exactitud (AP) y fotogramas por segundo (FPS) para velocidad.

**Resultados:** Un gran conjunto de datos etiquetado por un solo individuo (Conjunto de datos A) utilizado para entrenar un modelo Tiny YOLOv4 proporcionó los mejores resultados con un mAP medio de 0,95, una precisión de 0,86, una recuperación de 0,93 y 20 FPS.

**Conclusiones y relevancia clínica:** este novedoso modelo de detección de objetos tiene potencial de aplicación en el campo de la dermatología veterinaria.

## Résumé

**Contexte:** L'intelligence artificielle (IA) est utilisée avec succès en dermatologie humaine. L'IA utilise des réseaux neuronaux convolutionnels (CNN) pour accomplir des tâches telles que la classification d'images, la détection et la segmentation d'objets, facilitant ainsi un diagnostic précoce. La vision par ordinateur (VO), un domaine de l'IA, a donné d'excellents résultats dans la détection des signes de maladies cutanées humaines. Les maladies de la peau des pattes des chiens sont un problème courant dans la pratique vétérinaire générale, et les outils de vision par ordinateur pourraient faciliter la détection et le suivi des processus pathologiques. Actuellement, aucun outil de ce type n'est disponible en dermatologie vétérinaire.

**Animaux:** Des images numériques de pattes de chiens sains et de pattes présentant une pododermatite ou une néoplasie ont été utilisées.

**Objectifs:** Nous avons testé le nouveau modèle de détection d'objets Pawgnosis, un modèle d'analyse d'images Tiny YOLOv4 déployé sur un micro-ordinateur avec une caméra pour la détection rapide de la pododermatite et de la néoplasie canines.

**Matériaux et méthodes:** Les mesures de performance de prédiction utilisées pour évaluer les modèles comprenaient la précision moyenne moyenne (mAP), la précision, le rappel, la précision moyenne (AP) pour la précision, et les images par seconde (FPS) pour la vitesse.

**Résultats:** Un grand ensemble de données étiqueté par un seul individu (ensemble de données A) utilisé pour former un modèle Tiny YOLOv4 a fourni les meilleurs résultats avec une mAP moyenne de 0,95, une précision de 0,86, un rappel de 0,93 et 20 FPS.

**Conclusions et pertinence clinique:** Ce nouveau modèle de détection d'objets peut être utilisé dans le domaine de la dermatologie vétérinaire.