Recognising Activities of African Wild Dogs Using Machine Learning

UNIVERSITY OF Southampton

Group Design Project – Team 16

Charlie Steptoe – Aran McConnell – Rohan Bungre – Yue Kew

Supervisor: **Dr Srinandan Dasmahapatra**
2nd Examiner: **Dr Jize Yan**
External Partner: **Mafic Ltd**

Introduction

The African Wild Dog (Lycaon Pictus) is currently classified as an endangered species by the World Wildlife Fund, meaning conservation efforts are higher than ever before. This project proposed a process of classifying the activities of these dogs, by implementing machine learning techniques on canine movement data. A completed data processing pipeline will be used to demonstrate a proof of concept for use alongside nature documentary filmography supported by the project's external partner.

The project consisted of four main project phases: (1) Creation of a collar mount for Inertial Measurement Units, (2) Collection of 6-axis (Accelerometer & Gyroscope) data during dog activity sessions, (3) Data labelling using a predefined schema and (4) Creation of machine learning classification pipeline.

By creating a pipeline capable of classifying several key activities with accuracy, the project would allow for reduction of potentially intrusive camera setups used in nature filmography, as well as identifying behavioural patterns (ethologies) in a selected population of the species.

Mount Design

To collect movement data from dogs, a connecting mount was required to attach the existing device. Three mount designs were evaluated, and an eventual design chosen, based on ID tags worn by dogs in agility competitions. A prototype was 3D modelled, allowing the partner to adjust the model for African Wild Dogs as required.

The design was printed and tested concurrently with data collection. During testing a number of design faults were identified and adjusted for in the final design, as well as allowing for wireless charging through the mount casing.

The final design was exported to .stl format, as per the partner's standards, for printing and required changes.

Data Collection and Labelling

Circuits are designed with the aim of collecting 8 dog activities: Walking, Trotting, Galloping, Grooming, Barking, Eating, Sleeping and Hunting. A session would consist of several Designed circuits which are handpicked based on the dog category (pet or professionally trained) and its personality (calm or active).

For all sessions:

1) Dog collar with IMU sensor device attachment is worn by the dog.
2) The dog undertakes handpicked designed circuits.
3) Full process is filmed.
4) Sensor readings are automatically sent to AWS server when being charged.

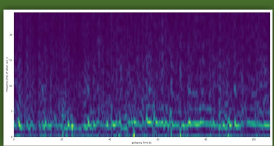
Once data of these activities was collected, the 6-Axis IMU data needed to be labelled as the activity occurring at that time. To do this we used a labelling tool provided by our customer, allowing us to label the data by viewing the video recorded alongside the 6-Axis data.

Feature Generation

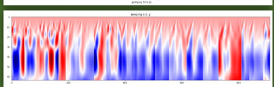
To extract the most information from the dataset, extra features were generated to increase the classification accuracy. Collected 6-axis raw IMU data (XYZ-axis linear & rotational acceleration) included large fluctuations and high-frequency perturbations that could disrupt the classification task.

To smooth the data, windows of approximately 400ms were used to calculate mean and variance values. To obtain directional information, bi-dependent features were generated using the values of X/Y, X/Z & Y/Z. This calculation is performed over the raw, unaveraged values, and resulting features were logarithmically scaled.

To obtain frequency information, a Fast Fourier Transform (FFT) over a 1.6 second window was performed, giving the frequencies' strengths for every time present in the data.



To obtain 'spiking' information at given time points a Wavelet Transform over a 1.6 second window was performed, producing values indicative of jumping, sniffing or eating.



AI Model Generation

To investigate the efficacy of various approaches to the activity classification problem, a total of seven different classifiers were analysed over a four-round, elimination performance comparison. The four rounds & metrics used were:

1) Raw Intra-session Accuracy
2) Unoptimised 'Leave-one-out' Session-wise accuracy
3) Optimised Mean Session-wise accuracy
4) Optimised Feature-reduced Session-wise accuracy

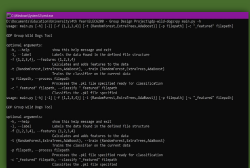
The multi-round elimination method was used to encourage efficient use of time whilst evaluating a large number of classifiers. As demonstrated, distinctions between session-wise and intra-session accuracy were required to mitigate overfitting. The full table of classifiers tested is shown here.

Classifier Name	Model Family
XGBClassifier	Ensemble (Gradient Boosting)
LGBMClassifier	Ensemble (Gradient Boosting)
HistGradientBoostingClassifier	Ensemble (Gradient Boosting)
ExtraTreesClassifier	Ensemble (Forest)
RandomForestClassifier	Ensemble (Forest)
MLPClassifier	Multi-layer Perceptron
KNeighboursClassifier	Nearest Neighbour

Deliverables

The team produced a Command Line Tool for our customer, combining the work carried out in Supervised Learning and Feature Generation. This tool allows a user to carry out the following functions:

- Label training data
- Add features to training data
- Train a classifier
- Process unlabelled data
- Classify activities in unlabelled data



The customer was also provided with CAD files of the Device Mount.

Future Work

To test the limitations of this project, more data than was collected would be required, preferably from African Wild Dogs, to evaluate the model's transferability to that domain, as well as improving classifier generalisation.

Results

The accuracies obtained using the 7 different classifiers is shown in the table below. For each classifier, the results of the first three rounds (Raw Accuracy, Generalised Accuracy, and Optimised Accuracy) are shown. Classifiers that have absent values were eliminated due to poor performance in a previous round.

Classifier	Raw Acc.	General Acc.	Optimised Acc.
XGBClassifier	99.67%	69.71%	61.58% ± 3.94%
LGBMClassifier	93.65%	59.03%	
HistGradientBoostingClassifier	96.92%	69.01%	58.84% ± 3.14%
ExtraTreesClassifier	99.99%	63.00%	
RandomForestClassifier	99.95%	72.39%	64.09% ± 3.10%
MLPClassifier	31.23%		
KNeighboursClassifier	86.58%	42.70%	

To compare how activities were classified against one another, a confusion matrix was created. This showed that activities were often confused within their "intensity class", with high intensity activities such as galloping and trotting, as well as activities consisting of similar poses (sniffing & eating) often being mistaken.