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Journal of Information Systems Applied Research

Identification of Stressed Wolf Populations Based on Hormone Levels Using Support Vector Machines (SVM)

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Abstract

In North America, wolf populations have been relentlessly hunted and persecuted since Europeans landed in the new world. In recent years, in an effort to restore the balance of flora and fauna in ecosystems, wolves have been reintroduced in some areas. In other areas, wolf populations are still hunted, based upon the premise of "managing them." Prior studies have suggested that physiological indicators, specifically elevated hormone levels, are symptomatic of higher stress levels in individual wolf subjects in heavily-hunted populations. This stress has far-reaching implications for reproduction, social structure and pack dynamics. The current study supports prior studies that used statistics to show elevated stress levels in hunted wolf populations and classification of individual wolf subjects as belonging to hunting-based stressed populations, based on physiological data, and by using machine learning.

Keywords: Machine Learning, data mining, Support Vector Machines, physiological indicators, Classification, Data Analytics

1. INTRODUCTION/LITERATURE REVIEW

Human caused mortality of predator populations (from hunting) has resulted in collateral negative effects on the impacted population (Coltman, 2003; Darimont 2009). The longstanding traditional objective of hunting has been the search for, and killing of, the strongest and fittest of the group or population, thereby reducing the reproduction of the healthiest members of the population. Evidence has shown that in the hunting of rams for trophies, there is a predominance of those of heavier weight and larger horn size (Festa-Bianchet et al., 2004, Coltman et al., 2003). These rams are of stronger breeding stock. Also, it was determined that they were of relative younger age, thereby having a negative impact on the reproduction rate of the populations (Coltman et al., 2002).

The intricate and complex social structure of wolf populations leads to an extreme vulnerability to additional increases in mortality and a derailment of pack behavior dynamics as a result of human intervention (Haber, 1996). Although wolf populations can recover from less severe and limited decreases in population, chronic pressures can negatively impact behavior, the foundation of social structure, and genetic capability. This combination of factors may reduce the possibility of group and pack recovery to sustainable and thriving levels. (Rausch, 1967; Haber, 1996;

Jezdrzejewski et al. 2005; Sidorovich et al., 2007; Rutledge et al., 2010, 2012).

Heavily-hunted wolf populations produce more female offspring (Sidorovich et al., 2007). Researchers have determined that genetic diversity in wolf populations is impacted by intense hunting (Jezdrzejewski et al., 2005). The social dynamics of neighboring wolf populations can be affected by the harvesting of wolves outside these protected areas (Rutledge et al., 2010). The mortality of wolf pups can increase, leading to reductions in the rate of population growth (Rausch, 1967).

The impact of hunting on population numbers can be easily determined, but accompanying physiological effects have not been measured or documented. It has been concluded that levels of hormones, like cortisol, are an indicator of increased stress in hunted individuals (Bateson & Bradshaw 2007). Also, stress can negatively affect the social behavior of a species population (Gobish et al., 2008).

Testosterone is a required component to male reproduction capability, but also has an effect on behavior. If an imbalance exists in the social structure, it is possible that testosterone may increase (Oliveria, 2004).

A number of studies have concluded that elevated levels of the hormones cortisol, testosterone, and progesterone in pregnant females are a reflection of the reproductive activity in the population (Foley et al., 2001). A relationship between female testosterone levels and the social structure of the populations has also been determined (Albert et al., 1991 & Bryan, et al., 2013).

More recently, researchers have looked at the changes in hormone levels as an indication of physiological effects of hunting by humans. One study has evaluated hormone levels in wolf populations to determine how human-caused mortality may impact group behavior, reproduction, and social dynamics. (Bryan et al., 2015). The researchers in this study concluded that elevated hormone levels can be found in subjects found in heavily-hunted wolf populations. Another study determined that, using machine learning, individual wolf subjects could be classified as belonging to either heavy or low hunting populations based on the level of these hormones (Stewart et al., 2021).

2. RESEARCH METHODOLOGY

In the current research we are attempting to further previous work to determine if additional machine learning methods might improve the accuracy of classification of wolf subjects based on hormone levels. As in the prior work, we are classifying individual wolf subjects as belonging to a heavily-stressed population due to hunting, or as a member of a population with lower hunting pressure. The criteria for determining stress is the measurement of hormones and reproductive steroids in the wolf’s fur. Similarly, we will evaluate the hormone levels of two separate wolf populations in Northern Canada studied previously (Bryan et al., 2015; Stewart et al., 2021).

The differences in these two wolf populations in this dataset is marked by the level of hunting. Wolves in the tundra-taiga area were heavily hunted using snowmobiles and firearms. Taiga is characterized by dense conifers, like spruce and pine. Conversely, tundra regions lack any tree cover. Wolves in the second area, boreal forests, had a lower level of mortality and were killed predominately by trapping. Boreal forests consist of deciduous and conifer trees, and experience wide-ranging temperatures over the course of the year (Musiani, M. & Paquet, P.C., 2004).

Bryan et al., (2015) concluded that elevated levels of stress and subsequent increased reproduction activity in the heavily hunted tundra-taiga wolves, were linked to high rates of hormone production (testosterone, progesterone, and cortisol). The researchers in the 2015 study compared the tundra-taiga wolves to wolves in areas of lower hunting pressure (i.e., the boreal forest), concluding statistical difference exists. (Bryan et al., 2015). In a prior work, we determined that classification of individual wolves in the same dataset was possible using machine learning, specifically k-nearest neighbor (Stewart et al., 2021). In this current work, our research questions are: 1) Can we determine the population that individual wolves belong to, based on the level of stress-related hormones using Support Vector Machines (SVM)?, and 2) Is this an improved method over k-Nearest neighbor in our prior work?

Sampling Method

The samples (n=148) were collected in a prior study in Nunavut, Northwest Territories and Alberta, Canada (Musiani et al., 2007). The samples (See Appendix, populations 1 and 2) consisted of wolf hair samples collected during the winter months. The process of extracting the hormones from the wolf hair, including quality control methodologies, is outlined in the Bryan et al., study (2015).

Bryan et al., (2015) used statistical analysis to differentiate the tundra-taiga wolves from the boreal forest wolves. The researchers used ANOVA and Welch's t-tests to compare the two wolf populations, concluding that wolves from the more heavily hunted populations had increased levels of reproduction and stress related hormones. They suggested that these physiological characteristics are in response to environmental factors, including human-induced mortality (Bryan et al., 2015).

The researchers proposed that confounding factors, specifically, ecological and genetic-based differences that could explain the gap in the level of hormones in the two populations. They concluded that the higher levels of cortisol in the tundra-taiga wolves could be attributed to long-term shortages in the food supply in summer, when wolves must travel farther to catch up with migrating caribou. Additionally, the massing of tundra-taiga wolf populations near caribou in summer causes interactions among wolves of different packs. (which could also explain the elevated levels of testosterone). The boreal wolves, conversely, have more traditional territories and stability, leading to fewer intergroup interactions (Walton, et al., 2001, Musiani et al., 2007).

To test the influence of these confounding factors, the researchers used a control group of wolves (n=30) from a heavily-hunted population in a boreal forest region (See Appendix, population 3). The hormone samples in the control group showed higher levels of cortisol than in the boreal forest populations. The wolves in the control group also had similar levels of cortisol as wolves in the heavily hunted northern tundra-taiga region. Therefore, the researchers concluded that higher cortisol levels are the result of increased mortality rates, possibly coupled with some habitat related factors (Bryan et al., 2015).

The current research seeks to determine and support the prior research on classification of the wolf subjects in this dataset. Prior work has answered the question as to whether human-exploited wolf populations are more heavily impacted physiologically (Bryan et al., 2015). And, an individual wolf can be classified to a population of hunted wolves by the level of specific hormones in the fur (Stewart et al., 2021). The current work expands upon this previous study and attempts to classify wolf subjects using Support Vector Machines (SVM).

Research Question

The research question to be evaluated in this study is as follows:

Can Individual wolves be classified into one of two populations, those belonging to a heavily-exploited population, or a member of a less-hunted group, based on hormone levels using SVM? SVM are a machine-learning methodology for classifying data points using an n-dimensional feature space (Cortes & Vapnik, 1995). SVM can be used to support the results obtained by two previous studies (Bryan et al., 2015; Stewart et al., 2021). That is, wolves can accurately be classified into one of two groups: 1) those with high levels of hunting-induced stress, and 2) those with less stress using SVM.

The objective of the current study is to determine whether the physiological consequences of hunting (as determined by levels of stress and reproductive hormones in hair, an indicator of elevated endocrine activity), can be used to classify wolves as belonging to a highly-stressed group or a less-stressed group.

To test our research question, we used data previously analyzed by Bryan et al., (2015) and SVM as the classification methodology to determine wolf membership in heavily stressed versus low stressed populations, based on hormone levels. The 2015 dataset included subject wolves from two separate areas and environments. The dataset contained 45 wolves from a lightly-hunted group in a northern boreal forest, and 103 wolves from a heavily-hunted Tundra-taiga forest area.

All samples were taken as part of a prior study (Musiani et al., 2007). The samples consisted of hair from the wolf subjects. Cortisol, testosterone, and progesterone (females) levels were measured in each hair sample. The data, listing population, gender, hair color, and levels of the three hormones can be found in the Appendix. In this work, unlike the 2021 study, we included fur color and gender variables in the analysis.

Support Vector Machines

SVM was used to compare cortisol and testosterone levels in the two different populations, and to determine the accuracy in classifying each subject into one of the populations, based on its hormone levels. Bryan et al., (2015) determined that higher levels of cortisol and testosterone were found in the tundra-taiga wolves and concluded that this higher level may be an indicator of social instability.

Due to the lower numbers of northern boreal forest wolves, stratified sampling was used. In addition, the data were partitioned into 70% for training and 30% for testing. A SVM linear model was developed using the Caret package in R, and 10-fold cross validation was used to improve accuracy and reduce over-fitting.

SVM algorithms are designed to find the optimum hyperplane in an N-dimensional space (N = the number of features) that separates, and most distinctly classifies, the data points (Figure 1).

There are a number of possible hyperplanes that can separate the two classes of the target variable. The goal is to determine the plane that has the maximum margin, (i.e., the maximum distance between data points of the different classes. Maximizing the margin distance elicits a higher level of confidence in the classification of new data points (Boser et al., 1992). The goal of classification using SVM then, is to determine the maximum separation between the possible outcomes of the classification of a target variable (i.e., two possible outcomes in this case).

SVM is a powerful classification method with the potential for high accuracy compared to other classification methods. It has wide application in classification, including cancer genomes (Huang et al., 2018), chemoinformatics and drug research (Rodríguez-Pérez, 2022), and even the classification of running technique between experienced and novice runners (Carter et al., 2022).

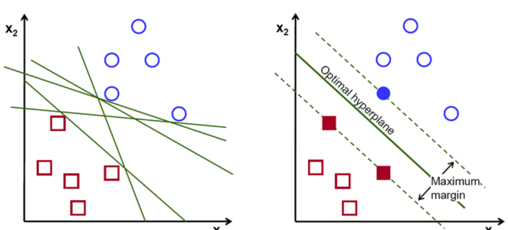

Figure 1: SVM determines the optimal hyperplane separating data points

3. RESULTS AND DISCUSSION

The results of our model yielded an accuracy of nearly 83% (as shown in Table 1). Additionally, the accuracy value is substantially above the No Information Rate, which indicates that the model is superior to simply choosing the dominant class from the target variable. Additionally, the Kappa (a measure of agreement between actual and predicted values, taking chance into account) is in a range that indicates good agreement. Considering all of the components in the aggregate, this suggests a markedly significant model with the capability of predicting the group an individual wolf subject belongs to, based upon the levels of cortisol and testosterone in the fur.

Measurement	Value
Accuracy	0.8276
Sensitivity	0.6667
Specificity	0.9412
Kappa	0.631
No Information Rate	0.5862

Table 1: Results of Classification of Wolf Subjects based on Cortisol and Testosterone Levels Using SVM

4. CONCLUSIONS

Past research on this topic has proposed that elevated levels of the hormones cortisol, testosterone, and progesterone in taiga-tundra wolves are explained by the synergistic effects of hunting pressures, the habitat, or sampling (Bryan et al., 2015). In the Bryan et al., study, the researchers compared cortisol levels in the taiga-tundra wolves to those of a control group of 30 wolf subjects (i.e., Little Smokey wolves) in a heavily-hunted boreal forest area in an effort to explain the differences in habitat and ecosystem characteristics. The results of this study showed statistically higher cortisol levels in both the Little Smokey and taiga-tundra wolves, compared to the northern boreal forest wolves.

Another study used the k-NN classification algorithm to show that individual wolves can be classified as belonging to heavily hunting-pressured groups based on cortisol and testosterone levels (Stewart et al., 2021). This classification was also shown to be at a highly-accurate level. That study also concluded that classification of female wolves (using the k-NN classifier) is possible with a favorable accuracy, based on the females' levels of progesterone.

Our results in the current work support the findings of Bryan et al., (2015) that showed statistically-significant differences in hormone levels between taiga-tundra and boreal forest wolf populations (i.e., heavily hunted vs. lightly trapped populations). Our results also support the results of Stewart et al., (2021) showing classification with high accuracy is possible in classifying hunting-stressed wolf subjects based on hormone levels.

Our findings support our suggestion that individual wolves can be classified as belonging to a heavily exploited population based on hormone levels using SVM. The similar results to the prior study using k-NN supports the use of machine learning models to classify the wolf subjects in this small dataset despite the relative imbalance in the target variable.

Prior studies have concluded that the potential implications of heavy human-caused mortality in wolves are substantive chronic stress, and diminished reproduction and breeding. The negative effects on breeding, compared with non-distressed populations are unclear. However, predictable genetic outcomes, as in the case with in-breeding, lack of diversity, increased disease, along with an elevated danger of population extinction are potential long-term impacts of heavy hunting (Leonard et al., 2005).

There are several implications revealed by the differences in hormone levels as determined by Bryan et al., 2015; Stewart et al., 2021), and this current work study. First, reproduction rates may be altered (and the social structure, along with the reproduction rates) when there is no longer a dominant pair (or pack hierarchy), and additional pack members are also breeding. The stability of the social group, characterized by a single litter per pack each year, is unbalanced (Haber, 1996). High levels of testosterone aid in any challenges an individual wolf may have within the social structure, where strength and dominance of the situation are necessary (Wingfield et al., 2001).

With a link between stress levels in wolf populations and human-based hunting, aside from the impact on wolf populations, the effects on entire ecosystems could be impacted. Wolves are recognized as a keystone species in their natural habitat (Boyce, 2018; Ripple & Beschta, 2012). Therefore, their absence or minimization can have far reaching impacts on entire ecosystems.

Limitations of Study

It should be noted that the sample size in this study was relatively small, particularly with the northern boreal forest wolves (i.e., n = 45). However, the research was unfortunately limited by the amount of available data. Additional machine-learning techniques and models could be employed in future studies to improve the results using methods to address unbalanced small datasets. These additional techniques might be used to determine whether we can improve the classification accuracy of wolf subjects, based on hormone levels as indicators of human-caused stress.

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APPENDIX A
Wolf Hair Data Collected during Musiani, et al. Study (2007)

Individual	Sex	Population	Colour	Cpgmg	Tpgmg	Ppgmg
1	M	2	W	15.86	5.32	NA
2	F	1	D	20.02	3.71	14.37622
3	F	2	W	9.95	5.3	21.65902
4	F	1	D	25.22	3.71	13.42507
5	M	2	D	21.13	5.34	NA
6	M	2	W	12.48	4.6	NA
7	M	1	W	26.78	4.58	NA
8	M	1	D	15.41	9.27	NA
9	F	1	D	33.87	4.81	19.9127
10	F	2	W	17.29	5.07	34.59806
11	F	1	W	9.43	4.47	25.88548
12	F	1	W	8.84	3.75	15.86882
13	F	1	D	34	4.76	33.08362
14	F	1	D	14.3	6.06	24.82876
15	M	1	D	12.16	5.75	NA
16	M	1	D	22.43	6.15	NA
17	F	2	W	26.26	4.93	25.00037
18	M	2	W	15.8	5.24	NA
19	M	1	W	7.93	4.14	NA
20	M	1	D	4.75	3.34	NA
21	M	2	W	9.17	4.02	NA
22	M	2	W	21.52	4.91	NA
23	M	1	W	10.79	3.91	NA
24	F	2	W	22.69	6.47	21.50033
25	F	2	W	22.17	4.28	31.8274
26	F	2	W	15.34	5.53	34.0765
27	F	1	W	20.48	5.06	20.21606
28	F	1	W	16.19	4.79	18.29115
29	F	1	W	24.05	3.7	21.29735
30	M	2	W	16.45	6.09	NA
31	F	2	W	21.91	4.19	36.40797
32	F	2	W	32.24	6.94	40.92793
33	F	2	W	23.99	5.97	45.9136
34	F	2	W	27.82	7.76	47.2674
35	F	2	W	19.83	6.55	40.93838
36	F	2	W	12.16	4.34	26.65583
37	F	2	W	19.05	6.34	23.90413
38	F	2	D	13.91	4.72	26.36326
39	F	2	D	17.16	9.25	34.64966
40	F	1	W	30.16	6.8	19.61885
41	F	2	W	24.38	5.49	28.12497
42	F	2	D	10.14	3.81	NA

43	M	2	W	18.4	4.98	NA
44	M	2	W	15.21	7.17	NA
45	M	2	W	24.64	15.13	NA
46	M	2	W	22.49	14.45	NA
47	M	2	W	17.42	5.36	NA
48	M	2	W	29.51	9.12	NA
49	M	2	W	27.3	10.75	NA
50	M	2	W	14.04	7.19	NA
51	M	2	W	11.77	5.17	NA
52	M	2	W	23.6	6.97	NA
53	M	2	W	18.14	5.7	NA
54	M	2	W	11.25	4.4	NA
55	F	1	W	14.82	10.81	NA
56	F	2	W	26.39	6.47	24.46521
57	M	2	W	15.15	4.52	NA
58	M	2	W	14.04	6.01	NA
59	M	2	W	21.39	7.36	NA
60	F	2	W	20.02	5.19	31.40929
61	M	2	W	24.64	14.08	NA
62	M	2	W	13.46	4.09	NA
63	M	2	W	18.79	9.74	NA
64	F	2	W	11.77	4.95	21.01472
65	F	2	W	19.96	7.62	28.06955
66	F	2	W	12.68	3.82	27.90797
67	F	2	W	19.76	5.26	27.37918
68	M	2	D	20.35	14.98	NA
69	F	2	W	17.68	5.97	53.28191
70	F	2	W	23.66	6.13	48.53432
71	F	2	W	17.23	7.24	NA
72	F	2	W	25.74	4.88	37.65696
73	F	2	W	19.89	6.35	31.90467
74	F	1	D	14.24	3.95	28.87637
75	M	2	W	17.55	5.02	NA
76	M	2	W	16.32	5.86	NA
77	M	2	W	15.34	5.78	NA
78	F	2	W	11.64	4.87	22.87393
79	M	2	W	13.65	5.04	NA
80	M	2	W	11.57	5.24	NA
81	M	2	W	20.35	5.98	NA
82	M	2	W	8.91	4.58	NA
83	M	2	W	9.1	4.4	NA
84	M	2	D	21.65	7.81	NA
85	M	1	D	10.6	3.65	NA
86	M	1	D	12.35	9.57	NA
87	F	1	D	7.93	3.83	16.77475
88	F	1	D	8	4.26	19.49892

89	F	1	D	7.61	4.24	22.56011
90	M	1	W	11.96	5.62	NA
91	M	1	D	14.82	5.35	NA
92	F	1	W	14.43	5.08	34.81566
93	F	1	D	19.57	6.81	16.67624
94	F	1	W	12.55	3.25	13.19328
95	F	1	D	12.61	3.54	13.62372
96	F	1	D	10.21	4.49	18.52082
97	M	1	D	15.99	5.82	NA
98	F	1	D	32.24	4.8	25.20981
99	M	1	D	15.41	5.68	NA
100	M	1	D	13.98	5.45	NA
101	M	1	D	16.32	6.65	NA
102	M	1	D	6.37	3.31	NA
103	M	1	W	8.19	3.81	NA
104	M	1	W	12.29	3.95	NA
105	F	2	W	12.16	4.37	13.17322
106	F	2	W	16.19	4.43	26.32807
107	F	2	W	11.83	3.48	16.40101
108	F	2	W	10.47	3.9	17.56024
109	F	2	W	21.13	5.09	29.29508
110	F	2	W	18.59	4.49	21.51784
111	F	2	W	12.09	3.96	28.49073
112	F	2	W	13	3.83	30.98607
113	F	2	W	12.09	4.65	28.62749
114	F	2	W	13.26	4.48	25.66584
115	F	2	W	12.03	4.32	19.28812
116	F	2	W	17.36	5.01	30.00925
117	F	2	W	18.14	3.56	12.7591
118	F	2	W	15.93	4.65	22.72246
119	F	2	W	12.29	5.01	23.24402
120	F	2	W	17.42	4.38	18.35924
121	F	2	W	13.2	5.3	18.88097
122	F	2	W	14.5	5.01	21.06504
123	F	2	D	11.44	4.04	16.154
124	M	2	D	11.57	5.68	NA
125	M	2	W	15.28	3.9	NA
126	M	2	W	13.46	5.1	NA
127	M	2	W	13.2	4.76	NA
128	M	2	W	11.25	4.89	NA
129	M	2	W	16.58	7.54	NA
130	M	2	W	13.2	5.07	NA
131	M	2	W	14.04	5.65	NA
132	M	2	W	17.03	5.81	NA
133	M	2	W	17.81	4.88	NA
134	M	2	W	12.48	4.86	NA

135	M	2	W	11.44	4.34	NA
136	M	2	W	40.43	9.13	NA
137	M	2	D	14.3	4.53	NA
138	M	2	W	14.89	4.32	NA
139	M	2	W	16.77	4.4	NA
140	M	2	D	9.95	4.31	NA
141	M	2	W	10.34	4.36	NA
142	M	2	W	20.54	8.06	NA
143	F	1	W	12.81	6.25	26.73429
144	F	1	W	16.51	4.62	28.10653
145	M	1	D	11.12	6.71	NA
146	M	1	D	11.64	4.51	NA
147	M	1	W	18.92	7.57	NA
148	M	2	W	19.89	5.35	NA
149	U	3		9.69	4.23	NA
150	U	3		19.37	4.26	NA
151	U	3		19.76	4.56	NA
152	U	3		11.31	7.73	NA
153	U	3		11.25	3.81	NA
154	U	3		13.85	4.28	NA
155	U	3		17.62	4.54	NA
156	U	3		22.82	4.34	NA
157	U	3		18.14	10.33	NA
158	U	3		13.52	8.12	NA
159	U	3		21.58	5.79	NA
160	U	3		8.91	29.74	NA
161	U	3		9.17	3.14	NA
162	U	3		14.17	10.32	NA
163	U	3		12.09	6.7	NA
164	U	3		54.47	61.79	NA
165	U	3		10.4	4.2	NA
166	U	3		50.31	5.48	NA
167	U	3		33.74	9.61	NA
168	U	3		14.76	8.94	NA
169	U	3		22.3	6.16	NA
170	U	3		23.21	10.59	NA
171	U	3		19.24	5.66	NA
172	U	3		13.07	4.4	NA
173	U	3		49.14	6.21	NA
174	U	3		73.19	6.41	NA
175	U	3		37.05	4.75	NA
176	U	3		16.45	7.29	NA
177	U	3		43.81	6.09	NA
178	U	3		14.89	3.53	NA