University of Ibadan
Journal of Science and Logics in ICT Research

Animals' Classification: A Review of Different Machine Learning Classifiers

*,1Olayinka O. Ogundile, *,2Ayoade A. Owoade, *,3Phebe B. Emeka and *,3Obaloluwa S. Olaniyan

Department of Computer Science, Tai Solarin University of Education, Ijagun, Ijebu-ode, P.M.B 2118, Ogun State, Nigeria.

1ogundileoo@tasued.edu.ng, 2owoadeaa@tasued.edu.ng, 3emekaphebe@gmail.com, obaloluwasamuel40@gmail.com

Abstract

Animal classification has recently attracted wide interest from ecologist. There have been attempts in the literature to apply image recognition methods to classify animals. The diversity in animal species with their intricate intra-class variability and interclass similarities cannot be accurately represented by these existing algorithms, despite their promising results for image recognition. This article strives to classify animals based on their different unique attributes, rather than using image recognition. Accordingly, the article evaluates the classification abilities of a few machine learning (ML) tools, including support vector machines (SVM), K-nearest neighbours (KNN), and decision trees (random forest (RF) and J48). The result was verified using the dataset taken from Irvine machine learning repository (University of California), which consists of 108 animals with 18 attributes. Besides, the performance of these ML tools was documented for different experimental conditions in terms of their classification accuracy (sensitivity) and classifier reliability (false discovery rate). The SVM classifier exhibits better false discovery rate and classification accuracy performance as compared to the KNN, J48, and RF classifiers. Yet, all of these ML tools can be deployed for real-time animal classification depending on end-user application requirements and formulations.

Keywords: *Animals' classification, DT, False discovery rate, J48, KNN, RF, SVM, Sensitivity*

1. INTRODUCTION

Ecologist has recently showed interest in animal detection and classification because of its benefit to the ecosystem. For instance, effective animal detection and classification can lessen the issues with wildlife road accidents that result in fatalities and injuries and improve human understanding of diversity [1]. Animal classification that focuses on the difficulty of differentiating between images of different animal species is a simple task for humans, but evidence suggests that even in situations where the distinction between cats and dogs is obvious, it is difficult to automatically make that determination [2]. Animals frequently make complex appearances in situations, and their flexible structures enable them to self-mask. In addition, much like any other item, they might appear in varied lighting conditions, perspectives, and scales; as such, it is challenging to detect and classify animals using images.

There have been attempts in the literature to apply image recognition methods to classify animals. The diversity in animal species with their intricate intraclass variability and interclass similarities cannot be accurately represented by these existing algorithms, despite their promising results for image recognition. For example, Perera and Collins [3] conducted research on recognizing different animal classes in a tracking tunnel by gathering ink footprints at a particular location. In Ukwuoma *et al* [1], a framework for the identification and classification of animal species based on a feature pyramid network and a modified multi-scale attention mechanism was proposed.

Olayinka O. Ogundile, Ayoade A. Owoade, Phebe B. Emeka and Obaloluwa S. Olaniyan (2023). Animals' Classification: A Review of Different Machine Learning Classifiers. *University of Ibadan Journal of Science and Logics in ICT Research (UIJSLICTR),* Vol. 9 No. 1, pp. 106 - 114

Several kinds of this approach for solving animal detection and classification problem have been proposed; yet, each one has its pros and cons.

This article strives to detect and classify animal based on their different attributes rather than using image recognition. Subsequently, the article reviews the classification performances of different machine learning (ML) tools; support vector machine (SVM), K-nearest neighbour (KNN) and decision trees (J48 random forest (RF)). The dataset taken from Irvine ML repository (University of California), which consists of 108 animals with 18 attributes is used to verify the performances of these ML tools.The performance of these ML tools are documented based on their sensitivity, Ψ (classification accuracy) and false discovery.

The relevance and contribution of this article is as follows. For a number of years, scholars have been very interested in the identification and classification of wildlife animals. Ecologists and, in particular, biologists frequently research animal behaviour in order to comprehend and foresee their actions. Moreover, animal detection has a variety of uses, including animal-vehicle accident avoidance, animal tracing, identification, anti-theft, and zoo animal security [4]. Presently it is tedious and time consuming for researchers identifying animals manually. The size of the dataset makes manual identification a difficult effort. More so, animals belonging to various classes may even resemble one another. For each of these problems, an effective algorithm for classifying animals is required, as presented in this article. In addition, developing system for classifying animals is a very challenging task. There have been numerous attempts to create an animal classification system. The majority of effort is observed to be done on small datasets. By easing the strain of manually analysing images, the use of machine learning to quickly and accurately classify wildlife might promote non-invasive sampling strategies in ecological investigations. This article reviews different automated and fast ML algorithms that can assist future robots in classifying animals according to their class type. Thus, future classification of animals can be easily achieved using the findings of this article based on the application requirements and formulations.

The remainder of this article is structured as follows. Section 2 explains some of the related works while pinpointing their difference from this article. A brief explanation of the ML tools used in this article are presented in Section 3. In Section 4, the dataset used for result verification is briefly discussed. This section also explains the unique attributes used for classification. The methodology used in developing the ML classifiers are discussed in Section 5. Section 6 presents the results and discussion for different experimental conditions. The article is concluded in Section 7 with discernible remarks.

2 RELATED WORKS

Many attempts have been made to automatically recognize animals in camera-trap images, but most of these depended on hand-designed features to achieve their task [5], [6]. A modified version of the work in Viola and Jones [7] was presented in Banks *et al* [8], where a real-time detection and tracking of animals was accomplished using a Haar-like detector. They proposed a model for tracking and noting the presence of an animal in a video and retrieved the lion's Haar-like properties. Only a single animal is used in Banks *et al* [8] to verify the result of their detector. But in this article, more than one animal is used to verify the performance of the deployed for ML classifiers.

In Kumar *et al* [4], a method for classifying animal images using a block-based methodology is proposed. To remove the background images from the provided image, segmentation was initially performed using a graph cut based method. The animal images that had been segmented were divided into a number of blocks, and the colour texture moments were then retrieved from the various blocks. For the classification, the probabilistic neural network and KNN were employed. An experiment was run using a dataset of 25 classes of animals, which included 4000 example images, to confirm the effectiveness of the proposed strategy. The experiment was carried out by randomly selecting images from the database to investigate the impact of classification accuracy, and the outcomes demonstrated that the KNN classifier performed better. In this article, the performance of the developed classifiers are verified on unique attribute rather than using animal images as documented in Kumar *et al* [4].

The survey in Prashanth and Sudarshan [9] combines an in-depth learning architecture with the identification of specific animals, which results in bounding boxes and precise appearance forms, as well as with the recognition of the actions of the animals. Camera traps for the tracking and analysis of many animal species can be employed with the resulting pipeline. Their work thoroughly examines and assesses a variety of architecture design alternatives, including cutting-edge techniques like flow-guided feature aggregation and region-based convolutional neural networks (R-CNN) mask. Whereas, Anshad [10] employed a deep learning algorithm to train a CNN on a fully annotated dataset made available on *Kaggle.com*, which included four distinct animal categories (Cheetah, Hyena, Jaguar, and Tiger), to recognize various animal species in the context of image classification used by ecologists and researchers. The network was implemented using deep learning and CNN algorithms. Multi-layers including imageInput layer, fully connected layer, SoftMax layer, and so on, were used to obtain a reasonable detection accuracy.

In Alharbi *et al* [11], a multiple feature predator animal identification method was proposed. The method concentrated on the animal's face, specifically the eyes and ears. The characteristics of 10 animals' ears and eyes were compiled into a database, and an experiment was run using machine learning methods like SVM and multi-layer perceptron (MLP) to categorize the animals as either pets or predators. The evaluation results showed classification accuracy for MLP and SVM of 82% and 78%, respectively, which to some part supports the efficacy of the proposed technique. However, in contrast to Ukwuoma *et al* [1], this article strives to classify animals based on some of their unique attributes or features using four different ML tools.

3. ML TOOLS

This article reviews the performance of different ML tools; SVM, KNN, J48 decision tree, and RF decision tree, used in the detection and classification of animals based on their unique attributes. As such, the rudiment of these ML tools are firstly briefly discussed.

3.1 Support Vector Machine (SVM)

One of the most used supervised machine learning models is the support vector machine (SVM). The goal of the SVM algorithm is to define the optimum decision boundary that can categorize the n-dimensional space, enabling us to quickly classify new data points in the future. Often, this best decision line is referred to as the hyperplane. SVM is frequently used to address regression and classification problems. It is suitable even when there are limited amount of training data, as it exhibits a better prediction accuracy [12].

3.2 K-Nearest Neighbour (KNN)

The K-nearest neighbors (KNN) method is an easy-to-use supervised machine learning strategy that can be used for both regression and classification problems [13]. The goal of the KNN technique is to calculate a function $h: U \rightarrow V$; such that, having an unknown observation u, $h(v)$ can positively predict the identical output y.

In applying the KNN for classification problem, the KNN algorithm essentially strives to compute the distance between all of the training points and the test data. Subsequently, it selects the nearest k points to the test data. KNN uses the distance metric equation defined in Eqn. (1) to calculate the distance of these points to the test data.

$$Đ = \sqrt{[(u_2 - u_1)^2 + \cdots + (v_2 - v_1)^2]} \quad (1).$$

Afterwards, the KNN algorithm calculates the likelihood that each of the k training data classes, j corresponds to the test data, as defined in Eqn. (2):

$$P(v = j | U = u) = \frac{1}{k} \sum_{i \in r} I(v^i = j), \quad (2)$$

where r is the set of k-nearest observations and $I(v^i = j)$) is an indicator variable that, if an observation (u_i, v_i) in r belongs to class j, evaluates to 1; otherwise, it evaluates to 0. Thus, the class with the highest probability is chosen.

3.3 Decision Tree (DT)

The supervised learning algorithm family also includes the decision tree (DT) algorithm. The DT algorithm can handle both classification and

Class_Number	Number_Of_Animal	Class_Type	Animal_Names
1	41	Mammal	aardvark, antelope, bear, boar, buffalo, calf, cavy, cheetah, deer, dolphin, elephant, fruitbat, giraffe, girl, goat, gorilla, hamster, hare,
2	20	Bird	chicken, crow, dove, duck, flamingo, gull, hawk, kiwi, lark, ostrich, parakeet, penguin, pheasant, rhea, skimmer, skua, sparrow, swan,
3	8	Reptile	pitviper, seasnake, slowworm, tortoise, tuatara, lizard, iguana, alligator
4	15	Fish	bass, carp, catfish, chub, dogfish, haddock, herring, pike, piranha, seahorse, sole, stingray, tuna, tilapia, eel
5	4	Amphibian	frog, newt, toad, salamander
6	10	Bug	flea, gnat, honeybee, housefly, ladybug, moth, termite, wasp, cricket, butterfly
7	10	Invertebrate	clam, crab, crayfish, lobster, octopus, scorpion, seawasp, slug, starfish, worm

Figure 1: Animal class details

animal_name	hair	feathers	eggs	milk	airborne	aquatic	predator	toothed	backbone	breathes	venomous	fins	legs	tail	domestic	catsize
aardvark	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1
alligator	0	0	1	0	0	1	1	1	1	1	0	0	4	1	0	0
antelope	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1
bass	0	0	1	0	0	1	1	1	1	0	0	1	0	1	0	0
bear	1	0	0	1	0	0	1	1	1	1	0	0	4	0	0	1
boar	1	0	0	1	0	0	1	1	1	1	0	0	4	1	0	1
buffalo	1	0	0	1	0	0	0	1	1	1	0	0	4	1	0	1
butterfly	0	0	1	0	1	0	0	1	0	1	0	0	0	0	1	0
calf	1	0	0	1	0	0	0	1	1	1	0	0	4	1	1	1

Figure 2: Selected Features

regression problems, just as other supervised learning algorithms. Decision trees are used in many different fields, including classification in scientific research, machine learning, information extraction, and bio-medical applications [14]. The goal of using a decision tree is to create a training model that can be used to predict the category or value of the target variable by learning simple choice rules derived from prior data. There are different types of decision tree techniques in the literature; however, this article focuses on the J48 decision tree and an ensemble decision tree method called random forest (RF).

3.3.1 J48

The J48 classifier is a classification algorithm that creates decision trees using the information theory principle [15]. The J48 is an extension of C4.5 algorithm that is implemented in Waikato environment for knowledge analysis (WEKA) using Java. The J48 generates a non-binary decision tree by using the gain ratio. In the J48 classifier, the dataset is divided based on the root node's value, which is determined by the features with the highest values. Each node calculates its gain value independently, and this computation process continues until all predictions have been made [16].

3.3.2 Random Forest (RF)

Random forest is composed of different decision trees in order to enhance the classification performance; as such, it is often referred to as an ensemble decision tree technique [17]. As opposed to relying just on one decision tree, RF uses forecasts from each tree and outputs the results based on the predictions that have gotten the most votes. Summarily, the working principle of the RF algorithm can be summarized in five steps.

1. From the training set, randomly choose t number of data points.
2. Develop the decision trees correlated with the chosen t.
3. Select q number of decision trees to be developed.
4. Redo 1 and 2.
5. Find the predictions for new data points from each decision tree, then place them in the category with the most votes.

4. DATASET AND ATTRIBUTE SELECTION

The dataset used for result verification is taken from Irvine machine learning repository (University of California), which consists of 108 animals with 18 attributes. The dataset is divided into two; the first dataset contains the class details of the animals used (that is, the class number, the number of animals in each

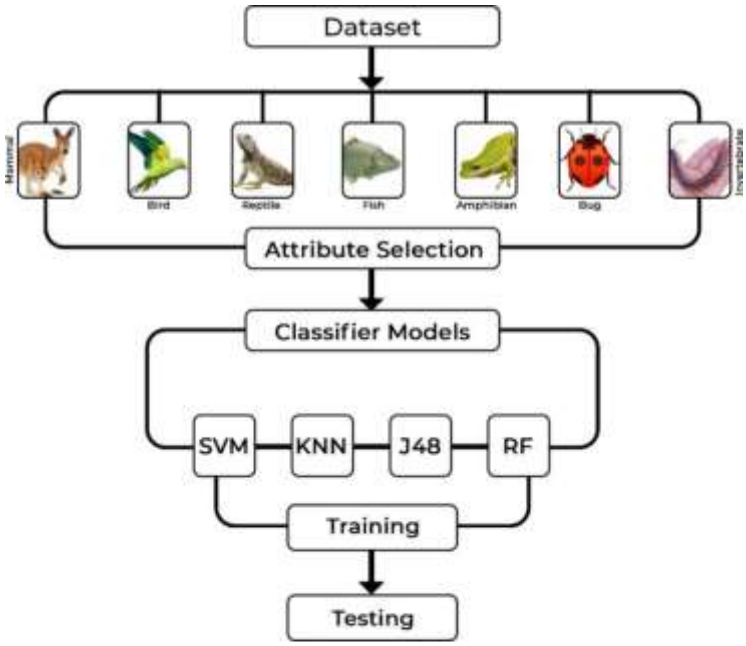

Figure 3: Classifier model

class, the class type and the animal names) as shown in Figure 1 while the second dataset contains the description of all the 108 animals according to the selected attributes as shown in Figure 2. Observing from Figure 1, the animals are grouped into seven (7) class types; Mammal, Bird, Reptile, Fish, Amphibian, Bug and Invertebrate. These class types have different number of animals. That is, 41 Mammals, 20 Birds, 8 Reptiles, 15 Fishes, 4 Amphibians, 10 Bugs and 10 Invertebrates. Similarly, observing from Figure 2, there are 16 features used in this article to classify these animals. This includes animal name, legs, eggs, hair, milk, backbone, airborne, aquatic, breathes predator, fins, venomous, toothed, tail, feathers, and cat-size. For example, if an animal lays egg, it is assign a 1; otherwise, it is assign a 0.

5. CLASSIFIER MODELS

Figure 3 depicts a simple flow diagram of the ML classifier system for animals. From the figure, the animal dataset is firstly gathered. Afterwards, distinctive features are manually selected from these animals by a human expect. These features are used to train the classifier model in preparation for testing and classification.

It is important to emphasize that four different classifier models are developed in this article; that is, SVM classifier, KNN classifier, J48 classifier and RF classifier. Accordingly, the selected attributes are used to train each classifiers separately. Results are therefore generated for each of the classifiers as documented in Section 6. The classifiers training and testing phase are performed using Python.

6. TEST RESULTS AND DISSCUSION

6.1 Sample Training and Testing

The dataset was firstly analysed manually, which contains 108 animals that falls in either of the seven classes mentioned earlier. Hence, the dataset was divided into two portions percentagewise. One portion (usually the smaller percentage) is used to train the classifier while the remaining portion is used for testing the performance of the classifier. In addition, we varied the size of the training, Ʈ portion; that is, Ʈ = 20%, 25% and 30%, to verify the performances of the classifiers for increase in Ʈ.

6.2 Performance Metrics

The performance of these developed automated classifiers are evaluated using two standard measurement metrics.

1. Sensitivity, Ψ: It is the ability of the classifier to correctly classify the animal. It can be represented mathematically as [18], [19], [20]:

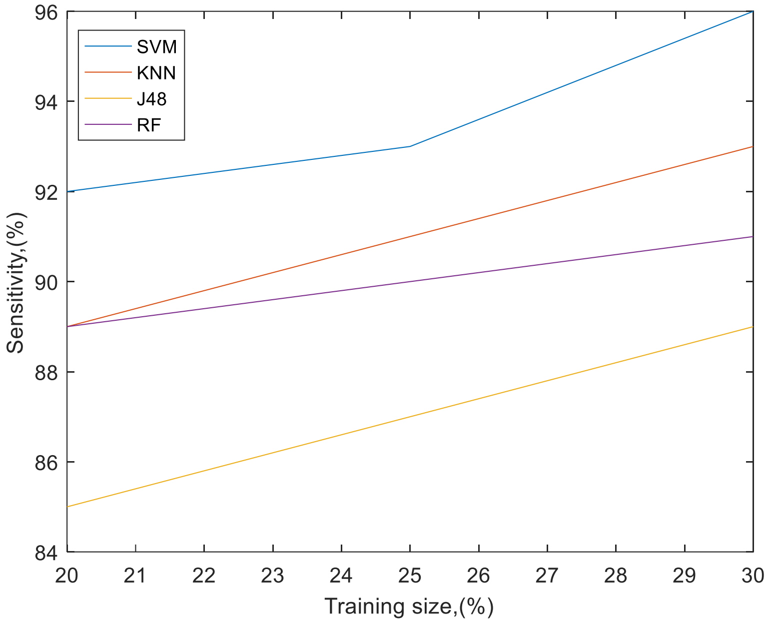

Figure 4: SVM, KNN, J48 and RF classifiers sensitivity performances for different Ʈ.

$$\Psi = \frac{TP}{TP + FN}, \qquad (3),$$

where TP (true positive) is the number of animal that were classified rightly and FN (false negative) is the number of times the automated classifiers missed that which was manually classified. Note that a high value of Ψ indicates a positive performance of the classifier.

2. False discovery rate, F: It measures the reliability of the automated classifier. It can be represented mathematically as [18], [19], [20]:

$$\mathrm{F} = \frac{FP}{FP + TP}, \qquad (4),$$

where FP (false positive) is the number of incorrect animal classification outputted by the classifiers. The lower the value of F the more reliable is the classifier.

6.3 Results Discussion

Tables 1, 2, and 3 shows the performances of the four classifiers for different training sizes. From Table 1 (Ʈ = 20%), the SVM classifier exhibited the best sensitivity performance in comparison to the KNN, J48 and RF classifiers. Similarly, the output of SVM classifier is the most reliable as compared to the KNN, J48 and RF classifiers, as it offers the lowest false discovery rate performance. Also observed from this table that the KNN and RF offers similar performance, which is better than the performance of the J48 classifier.

Table 1: Performance comparison of different animal classifiers:Ʈ = 20%.

	Ʈ = 20%	
Classifier	Ψ(%)	F(%)
SVM	92	0.33
KNN	89	0.37
J48	85	0.41
RF	89	0.38

Besides, consider Tables 2 and 3, the performance of all the classifiers increase with increase in the training size, Ʈ.. However, the SVM classifier offers superior Ψ and F performances in comparison with the other classifiers. Observe also that the Ψ and F performances of the KNN classifier surpasses that of the RF classifier as the Ʈ increases. Nonetheless, the RF offers better Ψ and F performances in comparison to the J48 classifier, which is envisaged. This is because the RF classifier is an ensemble DT technique, which is composed of different decision trees.

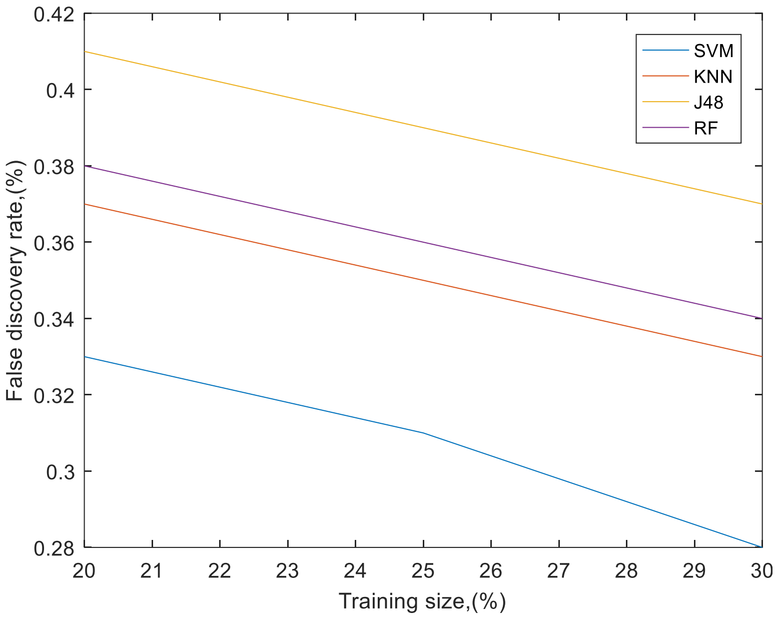

Figure 5: SVM, KNN, J48 and RF classifiers false discovery rate performances for different Ʈ.

Table 2: Performance comparison of different animal classifiers: Ʈ = 25%.

	Ʈ = 25%	
Classifier	Ψ(%)	F(%)
SVM	93	0.31
KNN	91	0.35
J48	87	0.39
RF	90	0.36

Table 3: Performance comparison of different animal classifiers: Ʈ = 30%.

	Ʈ = 30%	
Classifier	Ψ(%)	F(%)
SVM	96	0.28
KNN	93	0.33
J48	89	0.37
RF	91	0.34

To buttress the results in Tables 1, 2, and 3, Figures. 4 and 5 depict the Ψ and F performances of the classifiers respectively. Observe from Figure 4 as the Ψ performance of the classifiers increase with increase in the training size. But, the SVM exhibited the best performance as mentioned earlier. Likewise, in Figure 5, the F performance improves with increase in the training size. Remember, the lower the value of F the more reliable is the classifier. It is important this article mentions that a further increase in the training size will result in increase in the performance of the classifiers. Nevertheless, a point will be reached where further increase in the training size will no longer improve the performance of the classifier. Lastly, any of these classifiers can be deployed in real-time to classify animals based on their unique attributes or features, rather than using image recognitions.

7. CONCLUSION

This article presented a tutorial review of different ML classifiers for animals. It was documented that the SVM classifier obtained the best sensitivity and false discovery rate performances in comparison to the KNN, J48 and RF classifiers. The KNN classifier sensitivity and false discovery rate performances surpasses the decision tree (J48 and RF) classifiers. Whereas, the J48 classifier offered the worst sensitivity and false discovery rate performances. Irrespective of the result obtained, any of these classifiers can be used to classify animals depending on the application requirements and formation. More importantly, the article has established that animals can be classified based on their unique attributes, rather than using image recognition as deployed in most literature.

References

[1] Ukwuoma, C. C., Qina, Z., Yussif, S. B. Happy, M. N. Nneji, G. U. Urama, G. C. Ukwuoma, C. D. Darkwa N. B. & Agobaha, H., (2022). Animal species detection and classification framework based on modified multi-scale attention mechanism and feature pyramid network, *Scientific African*, 16, 1-18.

[2] Komarasamy, G., Manish, M., Vadde, D., Dhar, D. & Bhattacharjee, M., (2020). Automation of Animal Classification using Deep Learning, *International Research Journal of Engineering and Technology (IRJET)*, 7(6), 3455-3463.

[3] Achala Perera, T. A. S. & Collins, J., (2015). Imaged based species recognition system, *2015 9th International Conference on Sensing Technology (ICST), Aukland, New Zealand 2015, 195-199.*

[4] Sharath Kumar, Y. H., Manohar, N. & Chethan, H. K., (2015). Animal Classification System: A Block Based Approach, *International Conference on Advanced Computing Technologies and Applications*, 45(15), 336-343.

[5] Swinnen, K. R., Reijneirs, J., Brent, M. & Leirs, H., (2014). A novel method to reduce time investment when processing videos from camera trap studies, *PLoS One*, 9(6), 1-7.

[6] Figueroa, K., Camarena-Ibarrola, A., García, J. & Villela, H. T., (2014). Fast Automatic Detection of Wildlife in Images from Trap Cameras, *In: Bayro-Corrochano, E., Hancock, E. (eds) Progress in Pattern Recognition, Image Analysis, Computer Vision, and Applications. CIARP* 2014. Springer, Lecture Notes in Computer Science, 8827, 940-947.

[7] Viola, P., & Jones, M., (2001). Rapid object detection using a boosted cascade of simple features, *Proceedings of the 2001 IEEE Computer Society Conference on Computer Vision and Pattern Recognition. CVPR 2001*, Kauai, HI, USA, 2001, I-I.

[8] Banks, M. S., William, S. W., Jurgen, S., Jared, A., Parnell Q., & Goron, L. D., (2015). Why do animal eyes have pupils of different shapes? *Science advances*, 1(7), 10-11.

[9] Prashanth, C. R. & Sudarshan, T. S. B. (2020). Deep Learning Methods for Multi-Species Animal Re-identification and Tracking – a Survey, *Computer Science Review*, 38, 2020, 100289.

[10] Ahammed Anshad, K. A., (2020). Classification of animal's dataset from the Kaggle animals (cheetah, hyena, jaguar and tiger) database using neural network-based techniques and deep learning, *School of architecture, computing and engineering university of east London*.

[11] Alharbi, F., Alharbi, A. & Kamioka, E., (2019). Animal species classification using machine learning techniques, *MATEC Web of Conferences, 2018*, 2(3), 1-5, 277.

[12] Liu, Y., Feng, H., Li H. & Li, L., (2021). An Improved Whale Algorithm for Support Vector Machine Prediction of Photovoltaic Power Generation, *MDPI Symmetry*, 2021(13), 1-26.

[13] Akhil jabbar, M., Deekshatulu, B. L. & Priti Chandra, (2013). Classification of Heart Disease Using K-Nearest Neighbor and Genetic Algorithm, *Procedia Technology*, 10, 85-94.

[14] Vachiravel, S., (2015). Diagnosis of Heart Disease Using Decision Tree, *International Journal of Research in Computer Applications & Information Technology*, 2, 74-79.

[15] Sugumaran, V., Muralidharan, V. & Ramachandran, K. I., (2007). Feature selection using Decision Tree and classification through Proximal Support Vector Machine for fault diagnostics of roller bearing, Mechanical Systems and Signal Processing, 21(2), 930-942.

[16] Ashraf, N., Ahmad W. & Ashraf, R., (2018). A Comparative Study of Data Mining Algorithms for High Detection Rate in Intrusion Detection System, *Annals of Emerging Technologies in Computing*, 2(1), 49-57.

[17] Borges, F. A. S., Fernandes, R. A. S., Lucas, A. M. & Silva, I. N., (2015). Comparison between Random Forest Algorithm and J48 Decision Trees Applied to the Classification of Power Quality Disturbances, *Int'l Conf. Data Mining*, 146-147.

[18] Yao, R., Johnson, M., Clemins, P., Michael, D., Glaeser, S., Osiejuk, T. & Ebenezer, O.-N., (2009). A framework for bioacoustic vocalization analysis using hidden Markov models, *Algorithms*, 2, 1410–1428.

[19] Ogundile, O. O., Oloyede, M. O., Giwa, K. W. & Osanaiye, O. A., (2021). Performance Review of Machine Learning Techniques for the Detection of Humpback Whale Song, *International Journal of Information Processing and Communication*, 11(1), 51-58.

[20] Ogundile, O. O., Usman, A. M., Babalola, O. P. & Versfeld, D. J. J., (2021). Dynamic mode decomposition: A feature extraction technique based hidden Markov model for detection of Mysticetes' vocalisations, *Ecological Informatics*, 63(2021), 101306, 1-12.