INDIVIDUAL ANIMAL IDENTIFICATION FROM VIDEO

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Abstract

The problem of individual animal identification and re-identification from video frames and image collections is becoming increasingly significant, particularly in climate change. This paper addresses this problem by comparing different classifiers for recognizing individual animals in a dataset. The dataset comprises five annotated videos containing pigeons, koi fish, and pigs, with the training data consisting of the first half of each video. This paper aims to identify the individual animals in the second half of the video. The classifiers evaluated include the Largest Prior classifier, Linear Discriminant Analysis (LDA), 3-nearest neighbours (3-nn), Decision Tree, Support Vector Machine (SVM), Bagging, and Random Forest.

1 Introduction

The identification and tracking of individual animals from video frames and image collections have become increasingly important in the context of climate change. Understanding animal behaviour, population dynamics, and distribution patterns is crucial for effective conservation efforts and ecological monitoring as environmental conditions shift. However, traditional animal identification methods, such as manual observation and tagging, are often time-consuming, labour-intensive, and unsuitable for large-scale or continuous monitoring[4][13]. Video-based animal identification offers a promising solution by leveraging advancements in computer vision and machine learning techniques to automate the process[5].

Climate change impacts animal populations, including migration patterns, breeding behaviours, and habitat preferences[8]. These changes can have cascading effects on ecosystems and pose significant challenges for conservation biologists and ecologists[6][11]. Accurate and efficient identification of individual animals from video footage enables researchers to track individuals over time, study their behaviour, monitor population trends, and assess the impacts of environmental changes. This information is essential for understanding species' responses to climate change, identifying vulnerable populations, and implementing targeted conservation strategies[8].

This paper aims to explore and compare different classification methods for individual animal identification from video data. We will focus on data collected from five annotated videos containing pigeons, koi fish, and pigs, as these animals represent diverse taxa and have distinct characteristics and movement patterns. By analyzing this dataset and employing various classification techniques, we seek to evaluate the performance of different classifiers in accurately recognizing and re-identifying individual animals.

The specific objectives of this paper are as follows:

- First, investigate the effectiveness of different classifiers, including the Largest Prior classifier, Linear Discriminant Analysis, 3-nn, Decision Tree, SVM, Bagging, and Random Forest, for individual animal identification from video frames.
- Compare the performance of these classifiers in terms of accuracy, precision, recall, and F1-score.
- Assess the suitability of different feature representations, such as RGB features, hue histogram features (H10), Histogram of Oriented Gradients (HOG), and Local Binary Patterns (LBP), for animal identification from video data.

By achieving these objectives, this study aims to contribute to developing automated techniques for individual animal identification from video, facilitating efficient and reliable monitoring of animal populations in the face of climate change.

2 Related Work

Animal identification from images and video has been a topic of significant research interest in recent years. Camera traps, which are cameras placed in specific locations, along with videos captured without restrictions, provide valuable images that can be used to track animals, identify different species, and recognize individual animals[13]. In addition, numerous studies have explored various methodologies and techniques for automated animal recognition and re-identification. This section reviews relevant literature and discusses the general trends, methodologies, identified animals, and the topic's significance.

Previous research in Machine Learning has addressed various aspects of the problem, ranging from feature extraction and representation to classification algorithms. In addition, several studies have focused on applying machine learning techniques to recognize individual animals based on visual cues captured in videos or images[1][17].

The following literature review presents a comprehensive overview of relevant studies related to this paper's objectives.

2.1 Feature Extraction and Representation

Feature extraction plays a critical role in individual animal identification systems. Various visual features have characterized animals, including colour, texture, shape, and motion. For example, Atanboria et al. [5][3] proposed a method based on colour histogram features to distinguish individual birds in video data. Their results demonstrated high accuracy in identifying different individuals within a bird population. Similarly, many other researchers introduced a texture-based feature extraction approach using local binary patterns (LBP) to discriminate individual fish in underwater video sequences [15][14][18]. The LBP-based features captured distinct textural patterns, enabling effective recognition of individual fish.

2.2 Classification Methods

Different classification algorithms have been applied to animal identification tasks. The classifiers selected for comparison in this study are the Largest Prior classifier, Linear Discriminant Analysis (LDA), 3-nearest neighbours (3-nn), Decision Tree, Support Vector Machine (SVM), Bagging, and Random Forest. The Largest Prior classifier originates in the Bayesian probability theory [3][12].

LDA is a widely used linear classification algorithm that aims to maximize class separability by projecting the data onto a lower-dimensional space [16]. It has been successfully applied to various pattern recognition tasks, including animal identification [10]. 3-nn is a non-parametric classification algorithm that assigns a label to an unknown instance based on the labels of its nearest neighbours. Decision Tree algorithms, such as C4.5 [20][9], utilize a tree-like model to represent decision rules for classification. SVMs, popular for their ability to handle high-dimensional data, construct hyperplanes to separate different classes [7].

Ensemble learning methods, such as Bagging and Random Forest, have also been widely employed in individual animal identification tasks. Bagging combines multiple classifiers trained on different subsets of the data to improve the overall classification performance. Random Forest, an extension of Bagging, constructs an ensemble of decision trees and combines their predictions to achieve higher accuracy and robustness. Several studies have applied these classifiers to individual animal identification tasks. For example, Random Forest is useful for recognizing individual species from camera trap images [20][9]. The results demonstrated high accuracy and efficiency in identifying individual species based on distinctive characteristics. Similarly, Liu et al. [7] employed SVM for recognizing individual dolphins from underwater video footage. Again, the SVM classifier achieved promising results in accurately identifying different dolphins within a population.

2.3 Video Based Animal Identification

Video-based individual animal identification presents unique challenges compared to image-based approaches. The temporal aspect of video data provides additional information for accurate recognition. In addition, motion-based features and spatiotemporal patterns can be leveraged to improve classification performance. Atanbori et al. [4][5] proposed a video-based method for individual bird identification using a combination of appearance and motion features. By incorporating motion cues, they accurately distinguished individual birds in complex scenarios.

Furthermore, deep learning approaches have been applied to video-based animal identification tasks, utilizing convolutional neural networks (CNNs) to automatically learn discriminative features from video frames [1][19]. For example, Liu et al. [7] developed a deep-learning framework for individual fish recognition from underwater video sequences. The CNN-based approach performed better in accurately identifying individual fish, even in challenging environmental conditions.

3 Methodology and Experimental Setup

This section describes the methodology and experimental setup used for individual animal identification from video frames. The goal is to provide a detailed overview of the steps involved in the process, including the experimental setup, evaluation metrics, training and testing procedures and implementation details.

3.1 Experimental Setup and Evaluation Metrics

To conduct the experiments, we utilized a dataset consisting of five annotated videos containing pigeons, koi fish, and pigs. The videos were obtained from a public repository [2]. Each video was split into two based on the size description utilized in the code, with the first half as the training data and the second used for testing and identifying the individual animals.

To evaluate the performance of the classifiers, we employed several evaluation metrics commonly used in pattern recognition and classification tasks. These metrics include accuracy, precision, recall, and F1-score. Accuracy measures the overall correctness of the classifier's predictions, while precision focuses on the proportion of correctly identified instances among the predicted positive cases. Recall, also known as sensitivity, assesses the ability of the classifier to identify true positive instances, and the F1-score combines precision and recall into a single metric.

To check the balanced state of the dataset, a scan of the labels CSV file was carried out, which showed that the dataset was imbalanced for all the animals. We then factor in some resampling techniques using Synthetic Minority Over-sampling Technique (SMOTE) to cater to the dataset's imbalanced nature.

3.2 Training and Testing Procedures

The training and testing procedures were carried out using a supervised learning approach. The training data, consisting of the first half of each video, was used to train the classifiers to recognize individual animals. The testing data, comprising the second half of each video, was then used to evaluate the classifiers' performance in identifying the individual animals. The process was carried out for each of the four feature representations already extracted as RGB features (colour), hue histogram features (H10), HOG features (shape), and LBP features (texture).

3.3 Implementation Details

The entire experimental setup was implemented using the Python programming language. Python offers a wide range of libraries and tools for machine learning and computer vision, making it suitable for our purposes. We leveraged popular libraries such as sci-kit-learn, which provides a comprehensive set of classifiers and evaluation metrics. The Pandas and Numpy libraries were also used for loading and manipulating the data and computation of some classifier algorithms, respectively.The Smote and make_pipeline, were also imported from the imblearn library

By utilizing these libraries and tools, we ensured a robust and efficient implementation of the classification methods and evaluation procedures. In addition, each video/animal dataset for all four representations was trained and tested, and the metrics were captured accordingly. These details will be further explained in the result section of this paper.

4 Data Description

The dataset used in this paper on individual animal identification is from five annotated videos. These videos contain different types of animals, namely pigeons (three different species), koi fish, and pigs. The publicly available dataset can be accessed from the GitHub repository [2]. The dataset has been divided into training and testing sets, each serving a specific purpose in the classification task. The training data comprises the first half of each video (not an equally divided half), while the testing data consists of the second half. Consequently, the sizes of the training and testing sets vary for each video, as summarized in Table 1.

Each bounding box is an object in the data set of the respective video. Each column in the dataset is of quantitative(numerical) datatype. The dataset provides four different feature representations that have been extracted from the video frames: RGB features

Video Name	Training size	Testing size
Pigs_49651_960_540_500f	2710	3212
Koi_5652_952_540	916	719
Pigeons_8234_1280_720	2268	2291
Pigeons_4927_960_540_600f	1574	1303
Pigeons_29033_960_540_300f	2148	2241

Table 1: Shows the size split for the training and testing for each video/animal

(colour), H10-hue histogram features (colour), HOG features (shape), and LBP features (texture). These representations capture distinct aspects of the animals' appearance and characteristics, enabling a comprehensive analysis for identification purposes. The class labels for the individual animals in the dataset are provided in separate CSV files. The class labels are organized consistently, with each video having its respective class label file. For instance, the class labels for the video "Koi_5652_952_540" can be found in the file named "Koi_5652_952_540_Labels.csv". This organization facilitates the association between the annotated bounding boxes and their corresponding class labels.

During the analysis of the label files for each animal, a class count was performed, revealing that some classes have a minor representation compared to others. This indicates that the dataset suffers from class imbalance. Therefore, it is important to acknowledge and consider this imbalance during the implementation phase

5 Experiment and Result

This section discusses the code used in the individual animal identification and re-identification experiment and the outcome.

- First, all the required libraries were imported, like the Numpy, Pandas, sci-kit-learn for the classifiers and performance metrics.
- The class labels were analyzed to check whether the data was balanced; we discovered that the dataset from the five annotated videos were imbalanced, which was considered in the experiment, using the imblearn library.
- We created an instance of the SMOTE oversampling and initialized it with a specific random state value of 42.
- For each animal/video and representation, we specified the training and testing data split.
- Created a dictionary called classifiers that stores different classifier objects from sci-kit-learn

- Created a list called representations that stores the names of different data representations
  - "RGB": Represents the animal's RGB features (colour).
  - "HOG": Represents the animal's HOG features (shape).
  - "H10": Represents the animal's hue histogram features (colour).
  - "LBP": Represents the animal's LBP features (texture).
- We loaded each dataset with the corresponding labels. Converted from pandas dataframe to a numpy array for suitability with the scikit-learn classifiers
- The Largest Prior was computed using the NumPy function np.argmax to get the index of the maximum value in the array obtained from the count of the train_labels gotten using the np.bincount.
- We then created a pipeline with the SMOTE oversampling already initialized for each specified classifier. The pipeline is then trained on the training features and labels to predict the test features.

5.1 Results

The performance metrics for each animal by representation were printed and summarized in the below tables.

Video/Animal	Representation	Largest Prior	LDA	3-nn	Decision Tree	SVM	Bagging	Random Forest
Video: Pigs_49651_960_540_500f	RGB	Accuracy: 0.048,Precision: 0.002,Recall: 0.045,F1-score: 0.004	Accuracy: 0.358,Precision: 0.368,Recall: 0.343,F1-score: 0.316	Accuracy: 0.267, Precision: 0.239, Recall: 0.263, F1-score: 0.225	Accuracy: 0.16, Precision: 0.157, Recall: 0.155, F1-score: 0.135	Accuracy: 0.256, Precision: 0.252, Recall: 0.258, F1-score: 0.221	Accuracy: 0.189, Precision: 0.198, Recall: 0.183, F1-score: 0.171	Accuracy: 0.261, Precision: 0.251, Recall: 0.249, F1-score: 0.214
	HOG	Accuracy: 0.048,Precision: 0.002,Recall: 0.045,F1-score: 0.004	Accuracy: 0.218,Precision: 0.236,Recall: 0.209,F1-score: 0.189	Accuracy: 0.173, Precision: 0.298, Recall: 0.175, F1-score: 0.167	Accuracy: 0.121,Precision: 0.105,Recall: 0.11,F1-score: 0.103	Accuracy: 0.237,Precision: 0.37,Recall: 0.225,F1-score: 0.201	Accuracy: 0.152,Precision: 0.147,Recall: 0.216,F1-score: 0.136	Accuracy: 0.226,Precision: 0.234,Recall: 0.218,F1-score: 0.193
	H10	Accuracy: 0.048,Precision: 0.002,Recall: 0.045,F1-score: 0.004	Accuracy: 0.192,Precision: 0.163,Recall: 0.203,F1-score: 0.157	Accuracy: 0.171,Precision: 0.173,Recall: 0.179,F1-score: 0.164	Accuracy: 0.181,Precision: 0.173,Recall: 0.185,F1-score: 0.169	Accuracy: 0.188,Precision: 0.162,Recall: 0.201,F1-score: 0.157	Accuracy: 0.186,Precision: 0.176,Recall: 0.191,F1-score: 0.172	Accuracy: 0.201,Precision: 0.181,Recall: 0.206,F1-score: 0.178
	LBP	Accuracy: 0.048,Precision: 0.002,Recall: 0.045,F1-score: 0.004	Accuracy: 0.171,Precision: 0.154,Recall: 0.156,F1-score: 0.148	Accuracy: 0.135,Precision: 0.129,Recall: 0.12,F1-score: 0.119	Accuracy: 0.099,Precision: 0.095,Recall: 0.093,F1-score: 0.087	Accuracy: 0.099,Precision: 0.126,Recall: 0.089,F1-score: 0.094	Accuracy: 0.123,Precision: 0.116,Recall: 0.115,F1-score: 0.106	Accuracy: 0.165,Precision: 0.156,Recall: 0.158,F1-score: 0.138

Figure 1: shows the performance metrics for Pigs_49651_960_540_500f

As shown in Figure 1, all the feature representations for the pigs' datasets showed poor performance across all the classifiers, except for the LDA classifier on the RGB representation that showed slightly higher performance compared to others. Therefore, the feature representations used in this experiment may need to be better suited for accurately classifying the Pigs dataset.

Video/Animal	Representation	Largest Prior	LDA	3-nn	Decision Tree	SVM	Bagging	Random Forest
Video: Koi_5652_952_540	**RGB**	Accuracy: 0.056,Precision: 0.007,Recall: 0.125,F1-score: 0.013	Accuracy: 0.369,Precision: 0.262,Recall: 0.33,F1-score: 0.248	Accuracy: 0.206,Precision: 0.196,Recall: 0.155,F1-score: 0.147	Accuracy: 0.195,Precision: 0.198,Recall: 0.14,F1-score: 0.144	Accuracy: 0.312,Precision: 0.3,Recall: 0.316,F1-score: 0.251	Accuracy: 0.247,Precision: 0.24,Recall: 0.25,F1-score: 0.198	Accuracy: 0.337,Precision: 0.283,Recall: 0.293,F1-score: 0.256
	HOG	Accuracy: 0.056,Precision: 0.007,Recall: 0.125,F1-score: 0.013	Accuracy: 0.138,Precision: 0.173,Recall: 0.141,F1-score: 0.129	Accuracy: 0.1,Precision: 0.143,Recall: 0.084,F1-score: 0.093	Accuracy: 0.104,Precision: 0.118,Recall: 0.102,F1-score: 0.093	Accuracy: 0.093,Precision: 0.213,Recall: 0.118, F1-score: 0.077	Accuracy: 0.086,Precision: 0.106,Recall: 0.084, F1-score: 0.077	Accuracy: 0.125,Precision: 0.187,Recall: 0.139,F1-score: 0.119
	H10	Accuracy: 0.056,Precision: 0.007,Recall: 0.125,F1-score: 0.013	Accuracy: 0.432,Precision: 0.417,Recall: 0.358,F1-score: 0.354	Accuracy: 0.513,Precision: 0.52,Recall: 0.451,F1-score: 0.454	Accuracy: 0.538,Precision: 0.466,Recall: 0.467,F1-score: 0.423	Accuracy: 0.358,Precision: 0.385,Recall: 0.279,F1-score: 0.316	Accuracy: 0.618,Precision: 0.499,Recall: 0.518,F1-score: 0.479	Accuracy: 0.565,Precision: 0.493,Recall: 0.457,F1-score: 0.433
	LBP	Accuracy: 0.056,Precision: 0.007,Recall: 0.125,F1-score: 0.013	Accuracy: 0.22,Precision: 0.202,Recall: 0.196,F1-score: 0.184	Accuracy: 0.194,Precision: 0.215,Recall: 0.175,F1-score: 0.176	Accuracy: 0.157,Precision: 0.196,Recall: 0.155,F1-score: 0.143	Accuracy: 0.187,Precision: 0.205,Recall: 0.186,F1-score: 0.167	Accuracy: 0.157,Precision: 0.18,Recall: 0.163,F1-score: 0.144	Accuracy: 0.174,Precision: 0.224,Recall: 0.17,F1-score: 0.159

Figure 2: shows the performance metrics for Koi_5652_952_540

As shown in Figure 2, most of the classifiers performed fairly well in identifying the H10 representation of the Koi-fish, except the Large Prior Classifier. However, there is still room for improvement generally. The RGB, HOG and LBP representations show poor performance across all classifiers.

Video/Animal	Representation	Largest Prior	LDA	3-nn	Decision Tree	SVM	Bagging	Random Forest
Video: Pigeons_8234_1280_720	**RGB**	Accuracy: 0.096,Precision: 0.007,Recall: 0.077,F1-score: 0.013	Accuracy: 0.395,Precision: 0.465,Recall: 0.403,F1-score: 0.4	Accuracy: 0.331,Precision: 0.355,Recall: 0.326,F1-score: 0.317	Accuracy: 0.274,Precision: 0.257,Recall: 0.259,F1-score: 0.244	Accuracy: 0.41,Precision: 0.45,Recall: 0.386,F1-score: 0.378	Accuracy: 0.329,Precision: 0.366,Recall: 0.318,F1-score: 0.324	Accuracy: 0.377,Precision: 0.407,Recall: 0.355,F1-score: 0.348
	HOG	Accuracy: 0.096,Precision: 0.007,Recall: 0.077,F1-score: 0.013	Accuracy: 0.185,Precision: 0.242,Recall: 0.176,F1-score: 0.168	Accuracy: 0.223,Precision: 0.49,Recall: 0.208,F1-score: 0.227	Accuracy: 0.139,Precision: 0.149,Recall: 0.136,F1-score: 0.125	Accuracy: 0.184,Precision: 0.298,Recall: 0.17,F1-score: 0.163	Accuracy: 0.186,Precision: 0.238,Recall: 0.183,F1-score: 0.173	Accuracy: 0.218,Precision: 0.246,Recall: 0.199,F1-score: 0.185
	H10	Accuracy: 0.096,Precision: 0.007,Recall: 0.077,F1-score: 0.013	Accuracy: 0.342,Precision: 0.326,Recall: 0.338,F1-score: 0.309	Accuracy: 0.286,Precision: 0.281,Recall: 0.29,F1-score: 0.26	Accuracy: 0.205,Precision: 0.238,Recall: 0.218,F1-score: 0.191	Accuracy: 0.315,Precision: 0.299,Recall: 0.328,F1-score: 0.277	Accuracy: 0.222,Precision: 0.24,Recall: 0.237,F1-score: 0.208	Accuracy: 0.248,Precision: 0.281,Recall: 0.265,F1-score: 0.23
	LBP	Accuracy: 0.096,Precision: 0.007,Recall: 0.077,F1-score: 0.013	Accuracy: 0.188,Precision: 0.206,Recall: 0.176,F1-score: 0.166	Accuracy: 0.155,Precision: 0.209,Recall: 0.183,F1-score: 0.16	Accuracy: 0.15,Precision: 0.172,Recall: 0.159,F1-score: 0.142	Accuracy: 0.195,Precision: 0.227,Recall: 0.174,F1-score: 0.166	Accuracy: 0.19,Precision: 0.214,Recall: 0.192,F1-score: 0.172	Accuracy: 0.214,Precision: 0.259,Recall: 0.208,F1-score: 0.191

Figure 3: shows the performance metrics for Pigeons_8234_1280_720

As shown in Figure 3, the classifiers did fairly well in identifying the RGB and H10 representations more than the HOG and LBP representations across most classifiers excluding the Largest Prior for the Pigeons_8234_1280_720 dataset. However, the overall performance for the Pigeons dataset remains relatively low.

As shown in Figure 4, The classifiers performed worse on the Pigeons_4927_960_540_600f data set than the previous animal recognition performance.

As shown in Figure 5, the RGB identification rate was better with most of the classifiers like LDA, 3nn, Random Forest than other representations for the Pigeons_29033_960_540_300f dataset.

Video/Animal	Representation	Largest Prior	LDA	3-nn	Decision Tree	SVM	Bagging	Random Forest
Video: Pigeons_4927_960_540_600f	RGB	Accuracy: 0.035,Precision: 0.004,Recall: 0.111,F1-score: 0.007	Accuracy: 0.153,Precision: 0.185,Recall: 0.135,F1-score: 0.131	Accuracy: 0.08,Precision: 0.173,Recall: 0.07,F1-score: 0.084	Accuracy: 0.116,Precision: 0.159,Recall: 0.087,F1-score: 0.099	Accuracy: 0.092,Precision: 0.227,Recall: 0.073,F1-score: 0.092	Accuracy: 0.104,Precision: 0.189,Recall: 0.077,F1-score: 0.102	Accuracy: 0.124,Precision: 0.209,Recall: 0.103,F1-score: 0.125
	HOG	Accuracy: 0.035,Precision: 0.004,Recall: 0.111,F1-score: 0.007	Accuracy: 0.121,Precision: 0.236,Recall: 0.088,F1-score: 0.101	Accuracy: 0.078,Precision: 0.162,Recall: 0.084,F1-score: 0.066	Accuracy: 0.09,Precision: 0.082,Recall: 0.057,F1-score: 0.06	Accuracy: 0.148,Precision: 0.161,Recall: 0.103,F1-score: 0.109	Accuracy: 0.088,Precision: 0.111,Recall: 0.067,F1-score: 0.066	Accuracy: 0.127,Precision: 0.144,Recall: 0.115,F1-score: 0.105
	H10	Accuracy: 0.035,Precision: 0.004,Recall: 0.111,F1-score: 0.007	Accuracy: 0.058,Precision: 0.107,Recall: 0.049,F1-score: 0.062	Accuracy: 0.063,Precision: 0.097,Recall: 0.43,F1-score: 0.056	Accuracy: 0.072,Precision: 0.104,Recall: 0.044,F1-score: 0.06	Accuracy: 0.042,Precision: 0.108,Recall: 0.033,F1-score: 0.044	Accuracy: 0.075,Precision: 0.125,Recall: 0.052,F1-score: 0.071	Accuracy: 0.089,Precision: 0.165,Recall: 0.057,F1-score: 0.081
	LBP	Accuracy: 0.035,Precision: 0.004,Recall: 0.111,F1-score: 0.007	Accuracy: 0.122,Precision: 0.147,Recall: 0.114,F1-score: 0.103	Accuracy: 0.115,Precision: 0.138,Recall: 0.118,F1-score: 0.099	Accuracy: 0.091,Precision: 0.102,Recall: 0.072,F1-score: 0.074	Accuracy: 0.115,Precision: 0.094,Recall: 0.136,F1-score: 0.083	Accuracy: 0.108,Precision: 0.15,Recall: 0.098,F1-score: 0.096	Accuracy: 0.137,Precision: 0.183,Recall: 0.131,F1-score: 0.117

Figure 4: shows the performance metrics for Pigeons_4927_960_540_600f

Video/Animal	Representation	Largest Prior	LDA	3-nn	Decision Tree	SVM	Bagging	Random Forest
Video: Pigeons_29033_960_540_300f	RGB	Accuracy: 0.067,Precision: 0.004,Recall: 0.053,F1-score: 0.007	Accuracy: 0.51,Precision: 0.499,Recall: 0.5,F1-score: 0.456	Accuracy: 0.428,Precision: 0.425,Recall: 0.425,F1-score: 0.378	Accuracy: 0.283,Precision: 0.315,Recall: 0.279,F1-score: 0.255	Accuracy: 0.421,Precision: 0.456,Recall: 0.419,F1-score: 0.377	Accuracy: 0.358,Precision: 0.373,Recall: 0.352,F1-score: 0.321	Accuracy: 0.458,Precision: 0.459,Recall: 0.446,F1-score: 0.405
	HOG	Accuracy: 0.067,Precision: 0.004,Recall: 0.053,F1-score: 0.007	Accuracy: 0.38,Precision: 0.38,Recall: 0.339,F1-score: 0.319	Accuracy: 0.388,Precision: 0.431,Recall: 0.388,F1-score: 0.367	Accuracy: 0.164,Precision: 0.162,Recall: 0.152,F1-score: 0.148	Accuracy: 0.384,Precision: 0.393,Recall: 0.355,F1-score: 0.338	Accuracy: 0.237,Precision: 0.225,Recall: 0.216,F1-score: 0.209	Accuracy: 0.323,Precision: 0.358,Recall: 0.299,F1-score: 0.295
	H10	Accuracy: 0.067,Precision: 0.004,Recall: 0.053,F1-score: 0.007	Accuracy: 0.17,Precision: 0.172, Recall: 159,F1-score: 0.151	Accuracy: 0.225,Precision: 0.222, Recall: 214,F1-score: 0.199	Accuracy: 0.21,Precision: 0.222,Recall: 0.192,F1-score: 0.182	Accuracy: 0.22,Precision: 0.218,Recall: 0.197,F1-score: 0.186	Accuracy: 0.242,Precision: 0.239,Recall: 0.217,F1-score: 0.203	Accuracy: 0.231,Precision: 0.235,Recall: 0.212,F1-score: 0.2
	LBP	Accuracy: 0.067,Precision: 0.004,Recall: 0.053,F1-score: 0.007	Accuracy: 0.315,Precision: 0.309,Recall: 0.28,F1-score: 0.272	Accuracy: 0.242,Precision: 0.235,Recall: 0.209,F1-score: 0.207	Accuracy: 0.173,Precision: 0.167,Recall: 0.151,F1-score: 0.152	Accuracy: 0.144,Precision: 0.188,Recall: 0.128,F1-score: 0.119	Accuracy: 0.282,Precision: 0.246,Recall: 0.244,F1-score: 0.235	Accuracy: 0.326,Precision: 0.278,Recall: 0.284,F1-score: 0.264

Figure 5: shows the performance metrics for Pigeons_29033_960_540_300f

6 Conclusion

This paper comprehensively analyzed different feature representations and classifiers for animal identification in the given video data. The goal was to explore how different classifiers can recognize individual animals in the video data.

Based on the experimental results, we observed that the RGB representation consistently outperformed the HOG, H10, and LBP representations across most classifiers, except for the Koi-fish, where H10 performed best. This suggests that colour information is crucial in distinguishing animals in video data. Additionally, the Largest Prior consistently demonstrated the least performance compared to other classifiers tested. However, despite the efforts made, the overall performance of the classification models for the animal datasets remained relatively low. This indicates the need for further improvements in feature representations and classifier selection to achieve better results.

One possible avenue to improve the results is to explore more advanced feature extraction techniques tailored to video data. For instance, leveraging deep learning-based approaches, such as convolutional neural networks (CNNs)[7][1][19], to capture more intricate patterns and relationships in video frames, leading to enhanced classification performance. Another aspect to consider for future improvements is the size and quality of the dataset. Increasing the size of the dataset and ensuring a diverse range of animal species and environmental conditions could improve the generalization ability of the models.

The research conducted in this project holds significant importance and has the potential to impact various domains, especially in climate change. By automating the process of animal identification and monitoring, conservation efforts can be more effective and efficient. Furthermore, the techniques developed in this research can be extended to other areas, such as human activity recognition, object detection, and tracking in videos, thus broadening the scope of their applications.

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