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Performance Analysis of Image Recognition Techniques with Machine Learning Algorithms

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Abstract: Recent developments in machine learning engendered many algorithms designed to solve diverse problems in countless scientific areas, particularly recognition structures such as speech recognition, text recognition, image recognition. In image recognition tasks, the experiments within limited computing and time constraints are challenging issue. In this paper, we have recognized different types of bird's images and performance analysis of machine learning algorithms. Basic assembly of support vector machine, k-nearest neighbors, random forest and logistic regression are modified for experiments by defining relationships and adjusting different parameters. We have collected 3490 images of 22 types of bird's and created our dataset and the dataset is adopted to extract the features and the algorithms are employed for recognition of the different types of bird's images. The experimental results are discussed in terms of accuracy, Precision, recall and F1 score. While, the support vector machine better preforms as compared to the other three methodologies, whereas, KNN, RF and LR achieved more interesting results.

Keywords: Machine learning algorithms, Birds image recognition, create images dataset, Performance analysis.

1. INTRODUCTION

Image recognition was created to close the gap between computer vision and human vision by training the computer with data. Image recognition has recently grown in popularity among technology developers, especially with the growth of data in several industries such as surveillance, social media, engineering etc. Image recognition techniques are categorized into three types: (1) supervised recognition, (2) unsupervised recognition, and (3) semi supervised recognition. [1] Training is required for supervised recognition, which employs labeled data points and a known group of pixels.[1] When learned pixels are unavailable, or to put it another way, when training is not necessary and any random input can be used, unsupervised recognition is performed. [1] semi-supervised recognition combines the benefits of supervised and unsupervised recognition by utilizing unlabeled data points to eliminate the need for intensive domain scientist involvement and to mitigate bias caused by inadequate labeled data representation. [1] The main principle of an image recognizer is to use various mathematical techniques to recognize the feature in an image. Image recognition technology is a branch of artificial intelligence that consists of algorithms and statistical frameworks that enable the system to learn and predict specific function on its own [2]. Where it can think and act like a human. In very simple language, image recognition is a problem, and machine learning is a form of solution.

Zeeshan Khan, Sandeep Kumar, and Anurag Jain presented a paper titled Image Recognition Using Machine Learning Approach, in which they discussed various image recognition techniques such as KNN, RF, and SVM, as well as a full comparison of the techniques. They arrived at the conclusion that SVM produces better outcomes than the other techniques, but that SVM still has issues with feature outliers and the core problem, [3]. SVM [4] is one of the most effective methods for addressing many types of issues such as recognition and regression in the traditional machine learning areas. Ever et.al in [5] is to find the best approach for solving prediction issues utilizing various datasets and four machine learning algorithms. They came to the conclusion that while the amount of dataset samples does not directly affect algorithm performance, the properties of the dataset do.

Other surveys [6-8] have been conducted to find machine learning techniques for recognizing, collecting, and categorizing nonfunctional requirements in software documents. Recently, Iqbal. [8] A survey of machine learning algorithms and requirements engineering was presented. They provided a birds-eye view of how machine learning techniques can help with various requirements engineering tasks. The finding demonstrated that machine learning algorithms have an impact on software requirements elicitation, analysis, specification, validation, and management, among other aspects. The performance of four popular supervised machine learning algorithms on various datasets has been investigated in the paper [9]. The support vector machine algorithms had the maximum accuracy 99% across all datasets, whereas random forest and discriminant analysis had the weakest results. Many machine learning algorithms used in this paper are KNN (k-nearest neighbors) [10]. RF (random forest) [11]. SVM (support vector machine) [12]. LR (logistic regression) [13]. In [14], an automatic food detection system is utilized to detect and recognize varieties of Indian food using the KNN recognition model. A color and shape attribute are combined. The

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feature is recognized using the KNN recognition model. Lu et al. [15] conclude that SVM provides more accurate recognition of environmental sounds than KNN (k-nearest neighbors) and GMM (Gaussian Mixture Model). Mu et al. [16] for picking the best dataset, an automatic recognition approach combining principal component analysis and SVM was developed. For the text categorization challenge, Tong et al. [17] used a support vector machine. While using the support vector model for recognition, it discovered numerous significant features. However, in our study, we used a comprehensive set of SVM recognition techniques that are specifically tailored for text recognition. To get the best outcome in SVM recognition, a voting process is implemented. Image recognition is becoming one of the most important areas of machine learning study [18]. Due to issue such as distinct subclasses of birds varying dramatically in shape and appearance, the background of images, lighting conditions in images, and extreme fluctuation in the stance, recognizing bird classes from an image is a difficult task.

Machine learning models were employed by Kwan et al. [19] to classify 11 birds' classes. Mel-frequency cepstral coefficient were used to represent bird sounds. Kwan et al. also developed a system for automatic bird monitoring in the field. For the recognition of two birds' classes, Nadimpalli et al. [20] compare multiple image recognition algorithms. The HSV, GRAY, and RGB color spaces were all subjected to local thresholding. Burghardt et al. [21] describe a method for recognition African penguin birds based on chest pattern recognition. A light image is taken and evaluated for areas of interest, which are likely to contain a penguin chest.

Anderson et al. [22] and Kogan and Margoliash [23] were among the first to attempt to mechanically recognize bird types based on their sounds. For automatic song detection of Zebra Finches (Taeniopygia guttata) and In-digo punting, they used active time warping and hidden Markov models (Passerine Cyanea). A system based on an algorithm capable of recognizing traffic signals for the advantage of robotic vehicle navigation was developed by Yaong Yu et al. [24]. A mobile laser scanning (LMS) sensor is used in the system. Anuj Dutt and Aashi Dutt [25], use deep learning to implement Handwritten Character Recognition. Some machine learning algorithms, such as RF, KNN, and SVM, are included in this study. These three algorithms were trained and tested on the same dataset, allowing for a comparison of the three and an understanding of why deep learning is utilized in this critical situation. They discovered that the KNN approach with Yens or Flow has a 99.98% trained images accuracy and a 98.72% tested image accuracy.

The following section is described in this paper. Section 1 will cover the introduction and literature review used in this paper. The dataset descriptions used in this paper are described in section 2. The methodologies utilized in this paper are described in section 3. The results and discussion of the proposed work are described in section 4, and the paper concludes in section 5.

2. Dataset descriptions

Our dataset contains 3490 images of 22 different birds' species. In general, all machine learning techniques used as a 6:4 or 7:3 ratio for normal RGB images. Many researchers use an 8:2 ratio when working with HSI images [26]. Mostly dataset is divided into training and testing samples in the ratio 8:2 [27]. The total number of images is 3490, with 2791 used as training sets and the remaining 699 used as testing sets. Table: 1 summarizes the contained status of numbers in the training and testing sets to examine the performance of both models in recognizing all birds' images.

Table: 1 Training and testing samples

Label	Training samples	Testing samples	Total samples
Dove	26	6	32
Crow	42	11	53
Eagle	42	10	52
Myna	18	4	22
Parrot	70	18	88
Pigeon	19	5	24
Sparrow	34	9	43
Peacock	14	3	17
Hen	292	73	365
Duck	54	14	68
Owl	77	19	96
Quail	126	31	157
Robin	46	12	58

Swallow	130	33	163
Kite	158	40	198
Ostrich	355	89	444
Bat	70	18	88
Heron	110	27	137
Raven	270	67	337
Seagull	309	77	386
Woodpecker	235	59	294
Canary	294	74	368
Total Samples	2791	699	3490

The number of each class in the training set and testing set are different, as shown in the table above, and each number in the training set is 8:2 more than the number in the testing set. This ensures that the model may be fully trained on a variety of datasets before being tested

3. Methodology

Image recognition performance is improved using machine learning algorithms. Support vector machine, k-nearest neighbors, random forest, logistic regression are some of the machine learning algorithms discussed in this section.

3.1 Support Vector Machine

SVM (support vector machine) is a famous supervised machine learning algorithms originated by 1992. It's utilized for both recognition and regression problems. Because of its success in hand written character recognition, this algorithm became well-known. SVM has been shown to have a lower error rate in experiments [28]. Support vector machines are currently being reclassified as an important example of kernel methods a vital component of machine learning. The SVM algorithm's purpose is to find the optimum line or decision boundary for dividing n-dimensional space into classes so that new data points can be readily placed in the correct category in the future. A hyperplane is a name for the optimal choice boundary. The extreme points/vectors that assist to create the hyperplane are chosen via SVM. Support vector machine are extreme points, and this method is called a support vector machine.

3.2 K-Nearest Neighbors

KNN (k-nearest neighbor) is a basic and well-known gaining knowledge algorithm [29], originated by 1951. It's a supervised machine learning algorithms for used both recognition and regression problems. It is determined by the distance between the data points. The data points closest to each other are more comparable than those farthest apart. KNN has employed a variety of distance measures to determine data similarity. Some distance measurements commonly used in KNN are Euclidean distance, Manhattan distance, and City Block distance. The output class of a data is determined by the data that surrounds it, known as the neighbor. KNN has the advantage of being the easiest algorithm to implement. KNN works effectively with smaller data sets. However, with complex dataset, it can take a long time.

3.3 Random Forest

The supervised machine learning algorithm RF (random forest) is a famous machine learning algorithm. It can be utilized in machine learning for both recognition and regression problems. Random forests [30] is a decision tree-based ensemble recognizer. RF is a three-step ensemble learning algorithm that does the following: (1) bootstrapping a predictor variable- rich training dataset (2) A random selection of predictor variables was used to fit numerous recognition trees (3) integrating all of the trees forecasts each recognition tree divides the input recursively into binary groups that become progressively homogeneous to a specific class. About 37% of the data is ignored during the bootstrapping process, while the remaining data is simulated to bring the sample to full size. The recognition errors are calculated using the out-of-bag dataset, which is an internal cross-validation technique in the RF algorithm. When it comes to recognition problems RF outperform recognition problems.

3.4 Logistic Regression

LR (logistic regression) is a supervised learning algorithms that is one of the most famous machine learning algorithms. It can be used for both recognition and regression, however, it is most commonly employed for binary recognition. This logistic regression binary class recognition could be expanded to multi-class recognition. For multi-class recognition, a method known as 'one-vs-all' is utilized, in which a binary recognition is conducted for each class. Different parameters, such as alpha or learning rate, epoch or number of iterations, influence logistic regression. When all of these parameters are set correctly, good recognition results are obtained.

4. Results and Discussion

The performance of our proposed method was evaluated using 3490 images from 22 different bird classes from our dataset. Four different machine learning algorithms were applied. With respect to various parameters, all of the algorithms provide distinct types of performance. We utilized a poly kernel for SVM. SVM provides 95% accuracy without any parameters. Table: 2 and the flow chart in Figure: 1 exhibit the performance accuracies of several machine learning algorithms.

Table 2. Accuracy table

Machine learning algorithms	Accuracy Rate
SVM(Poly)	0.95
KNN	0.91
Random forest (Gini)	0.93
Logistic regression	0.90

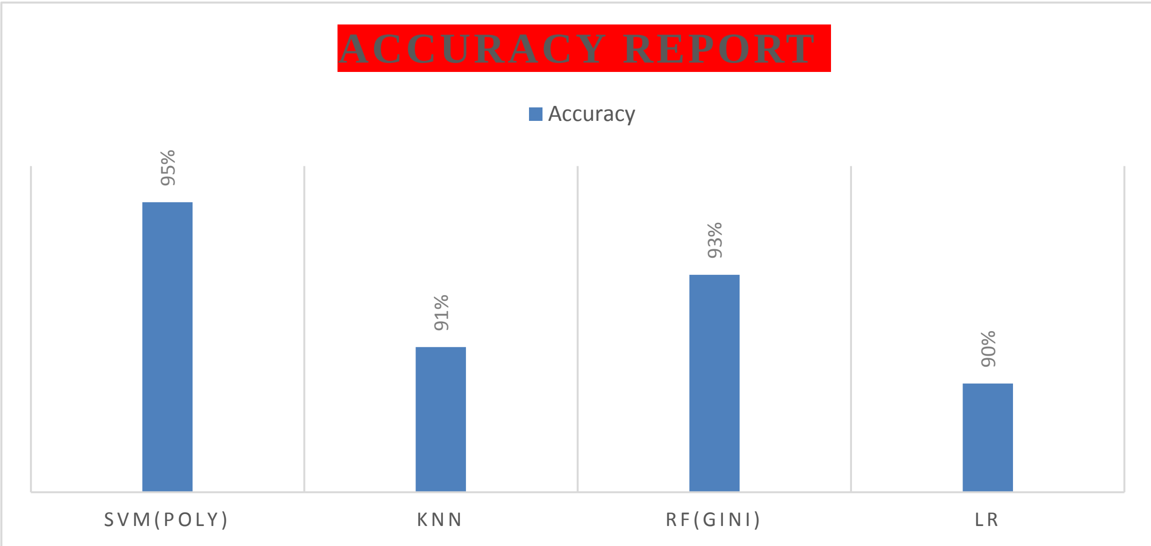


Fig: 1 Accuracy Report

The implementation of SVM with poly kernel yields the highest accuracy of 95%, followed by random forest at 93% accuracy as shown in Fig: 1. When using K-NN and logistic regression, accuracies of 91% and 90% were obtained, respectively.

The recognition algorithms performance was assessed using a variety of well-known results such as accuracy, precision, recall, and F1 score. We use confusion matrix to determine the precision, recall, F1 score and other metrics. The confusion matrix is a typical performance measure for recognition algorithms, with the rows representing the output or predicted class and the columns representing actual or targeted class. To assess the algorithms performance, we used test data. Finally, we presented a graphical representation of the performance of machine learning algorithms in the recognition of bird images. This was accomplished using a grouped bar graph. The bar graph depicts the results of all recognition methods. The experimental outcomes for each class are displayed on the horizontal axis, while the classes are displayed on the vertical axis. The results shows that SVM produces the best outcomes, while logistic regression produces the worst. Table: 2 displays the outcomes. Fig: 1 shows the confusion matrix for various recognition methods, while Fig: 2 shows recognition reports for various machine learning algorithms.

Predicted Class / **Actual Class**	**Dove**	**Crow**	**Eagle**	**Myna**	**Parrot**	**Pigeon**	**Sparrow**	**Peacock**	**Hen**	**Duck**	**Owl**	**Quail**	**Robin**	**Swallow**	**Kite**	**Ostrich**	**Bat**	**Heron**	**Raven**	**Seagull**	**Woodpecker**	**Canary**
Dove	12	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Crow	0	11	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0
Eagle	0	0	4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Myna	0	0	0	17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Parrot	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pigeon	0	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sparrow	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Peacock	0	0	0	0	0	0	0	70	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Hen	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0
Duck	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0
Owl	0	0	0	0	0	0	0	0	0	1	35	0	0	0	0	0	0	0	0	0	0	0
Quail	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0
Robin	0	0	0	0	0	0	0	0	0	0	0	0	36	0	0	0	0	0	0	0	0	0
Swallow	0	0	0	0	0	0	0	0	0	0	0	0	0	36	0	0	0	0	5	0	0	0
Kite	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91	1	0	1	0	0	0	0
Ostrich	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	11	0	0	0	1	1	0
Bat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	16	0	1	1	1	0
Heron	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	63	0	0	0	0
Raven	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	1	0	70	0	0	0
Seagull	0	0	0	0	0	0	0	0	0	0	0	0	0	2	3	1	0	1	4	47	0	0
Woodpecker	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	76	0
Canary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63

a) Support vector machine confusion matrix(poly)

Predicted Class / **Actual Class**	**Dove**	**Crow**	**Eagle**	**Myna**	**Parrot**	**Pigeon**	**Sparrow**	**Peacock**	**Hen**	**Duck**	**Owl**	**Quail**	**Robin**	**Swallow**	**Kite**	**Ostrich**	**Bat**	**Heron**	**Raven**	**Seagull**	**Woodpecker**	**Canary**
Dove	12	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Crow	0	12	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Eagle	0	0	4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Myna	0	0	01	15	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Parrot	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pigeon	0	0	0	0	1	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sparrow	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Peacock	0	0	0	0	0	0	0	69	0	0	1	0	1	0	0	0	0	0	0	0	0	0

Hen	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0
Duck	0	0	0	0	0	0	0	0	0	19	3	0	0	0	0	0	0	0	0	0	0	0
Owl	0	0	0	0	0	0	0	0	0	2	34	0	0	0	0	0	0	0	0	0	0	0
Quail	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0
Robin	0	0	0	0	0	0	0	0	0	0	0	1	35	0	0	0	0	0	0	0	0	0
Swallow	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	10	0	0	0
Kite	0	0	0	0	0	0	0	0	0	0	0	0	0	0	91	0	0	2	0	0	0	0
Ostrich	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	9	0	0	0	1	0	0
Bat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	1	3	1	0	0
Heron	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	64	0	1	0	0
Raven	0	0	0	0	0	0	0	0	0	0	0	0	0	4	1	0	2	0	69	1	0	0
Seagull	0	0	0	0	0	0	0	0	0	0	0	0	0	4	3	0	3	1	7	39	1	0
Woodpecker	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	1	76	0
Canary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63

b) K-Nearest Neighbors confusion matrix

Predicted Class / **Actual Class**	**Dove**	**Crow**	**Eagle**	**Myna**	**Parrot**	**Pigeon**	**Sparrow**	**Peacock**	**Hen**	**Duck**	**Owl**	**Quail**	**Robin**	**Swallow**	**Kite**	**Ostrich**	**Bat**	**Heron**	**Raven**	**Seagull**	**Woodpecker**	**Canary**
Dove	12	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
Crow	0	13	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Eagle	0	0	4	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Myna	0	0	0	16	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
Parrot	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pigeon	0	1	0	0	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sparrow	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Peacock	0	0	0	0	0	0	0	71	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Hen	0	4	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0
Duck	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0
Owl	1	0	0	0	0	0	0	0	0	3	32	0	0	0	0	0	0	0	0	0	0	0
Quail	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0

Robin	0	0	0	0	0	1	0	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0
Swallow	0	0	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	1	7	0	0	0
Kite	0	0	0	0	0	0	0	0	0	0	0	0	0	0	89	0	0	3	0	0	1	0
Ostrich	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	6	0	0	0	3	1	0
Bat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	15	1	2	1	0	0
Heron	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	64	0	0	0	0
Raven	0	0	0	0	0	0	0	0	0	0	0	0	0	7	1	0	0	0	68	1	0	0
Seagull	0	0	0	0	0	0	0	0	0	0	0	0	0	3	2	0	2	2	3	45	1	0
Woodpecker	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	78	0

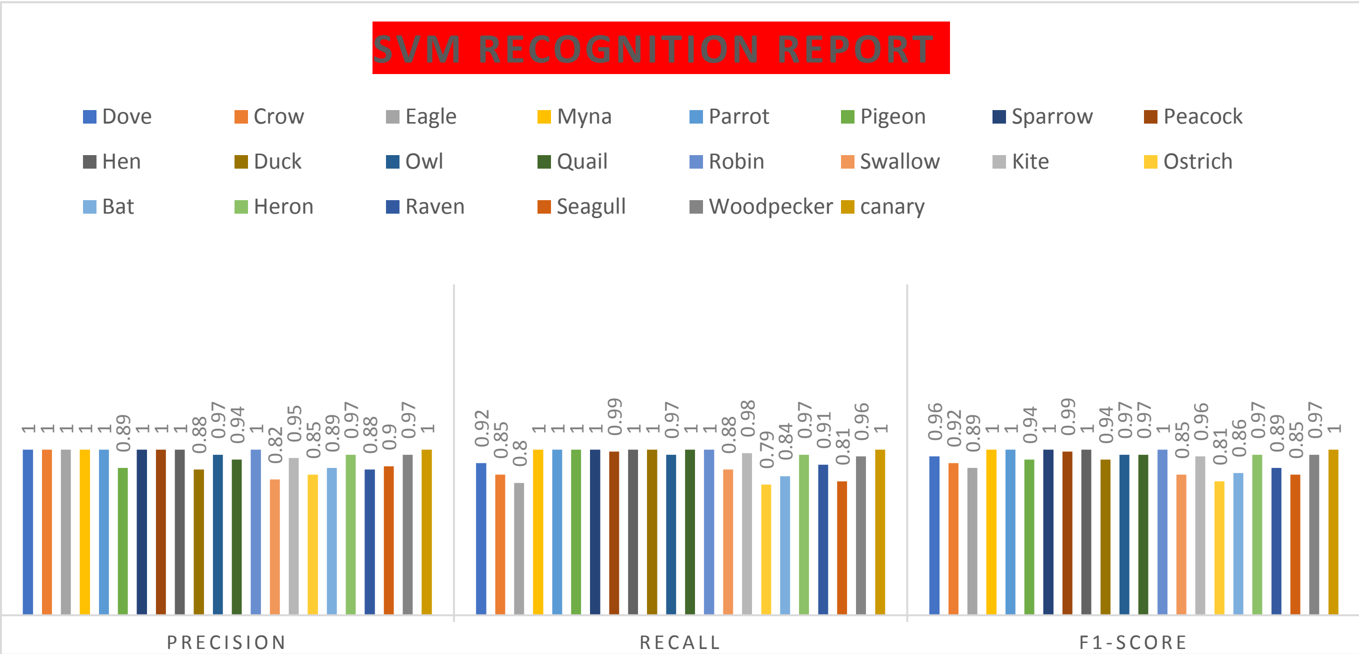
c) Random forest confusion matrix (Gini)

Predicted Class / **Actual Class**	**Dove**	**Crow**	**Eagle**	**Myna**	**Parrot**	**Pigeon**	**Sparrow**	**Peacock**	**Hen**	**Duck**	**Owl**	**Quail**	**Robin**	**Swallow**	**Kite**	**Ostrich**	**Bat**	**Heron**	**Raven**	**Seagull**	**Woodpecker**	**Canary**
Dove	12	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Crow	0	12	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Eagle	0	0	4	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Myna	0	0	0	15	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Parrot	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pigeon	0	0	0	1	0	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sparrow	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Peacock	0	0	0	0	0	0	0	70	0	0	1	0	0	0	0	0	0	0	0	0	0	0
Hen	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0
Duck	0	0	0	0	0	0	0	0	0	22	0	0	0	0	0	0	0	0	0	0	0	0
Owl	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	1
Quail	0	0	0	0	0	0	0	0	0	0	0	17	0	0	0	0	0	0	0	0	0	0
Robin	0	0	0	0	0	0	0	0	0	0	0	1	35	0	0	0	0	0	0	0	0	0
Swallow	0	0	0	0	0	0	0	0	0	0	0	0	0	33	1	0	0	1	5	0	1	0
Kite	0	0	0	0	0	0	0	0	0	0	0	0	0	0	86	1	2	0	1	2	1	0
Ostrich	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	8	1	0	0	2	0	1
Bat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	13	0	3	1	1	0
Heron	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	58	0	1	4	0

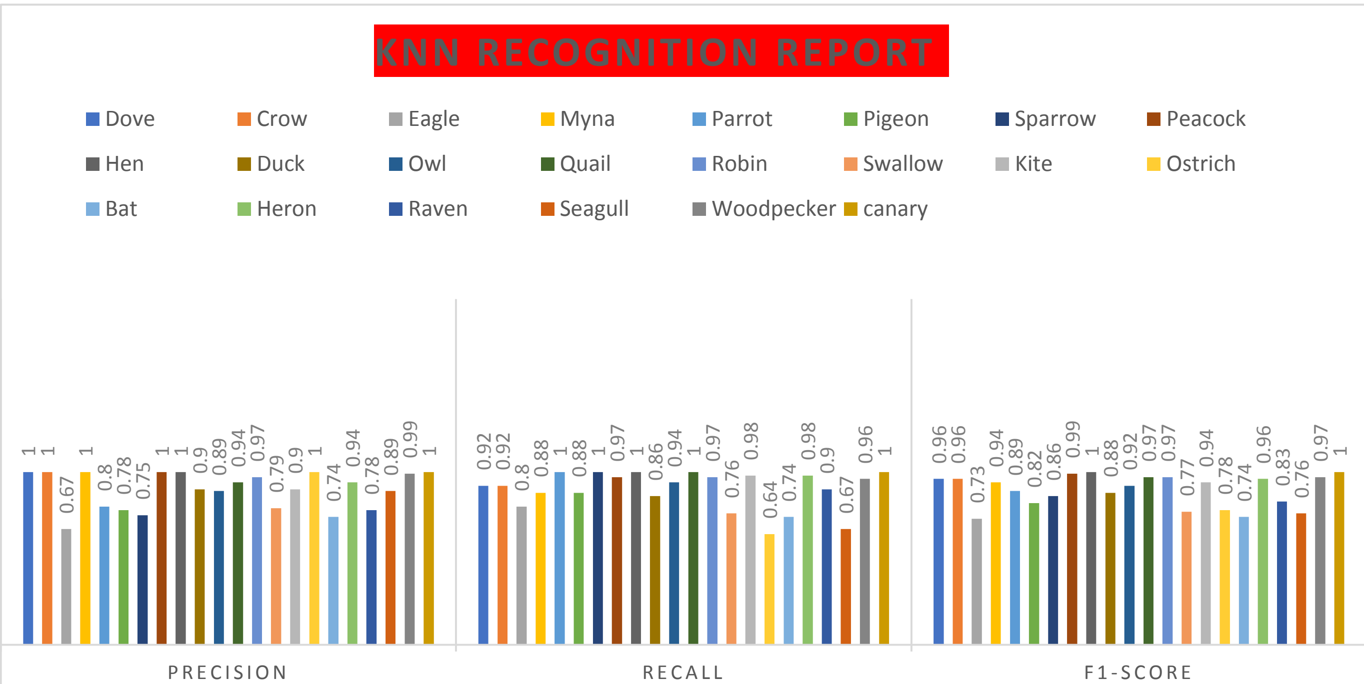
Raven	0	0	0	0	0	0	0	0	0	0	0	0	0	4	2	0	1	0	68	2	0	0
Seagull	0	0	0	0	0	0	0	0	0	0	0	0	0	3	3	0	3	1	2	44	2	0
Woodpecker	0	0	0	0	0	0	0	0	0	0	0	0	0	0	7	0	0	1	0	1	70	0
Canary	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	63

d) Logistic regression confusion matrix

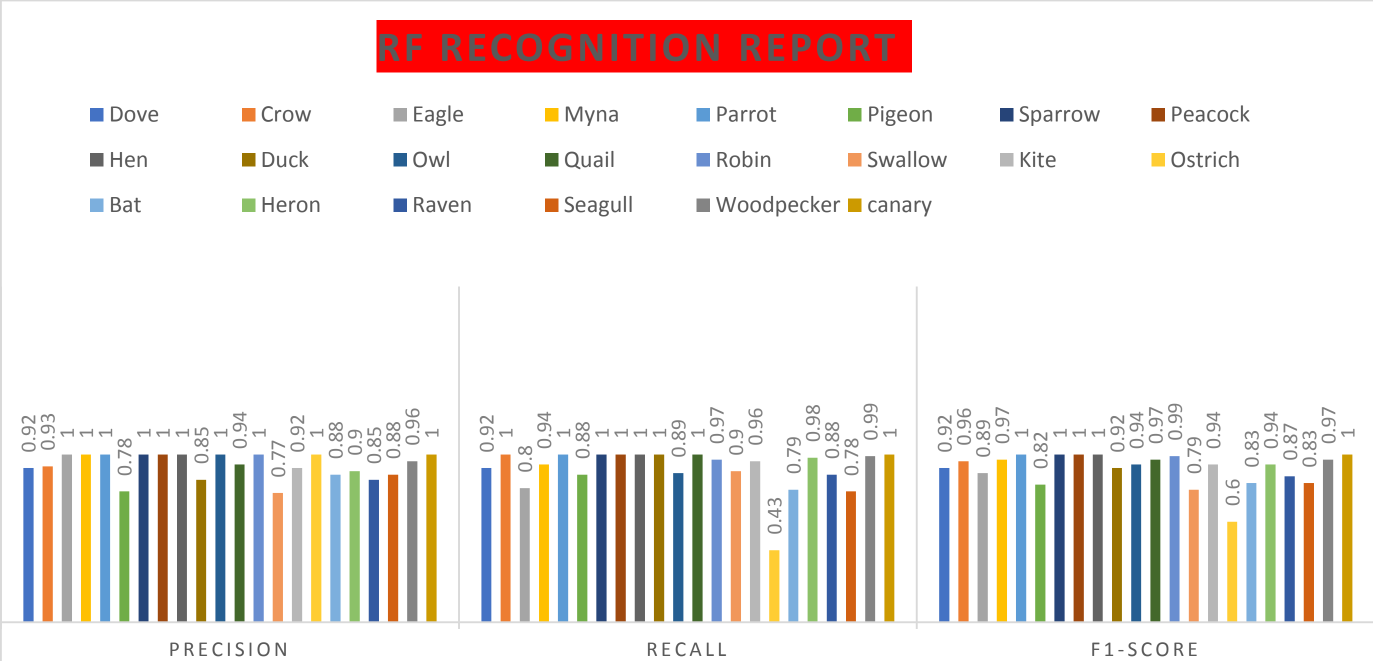
Fig. 2. Confusion Matrix of recognition method.



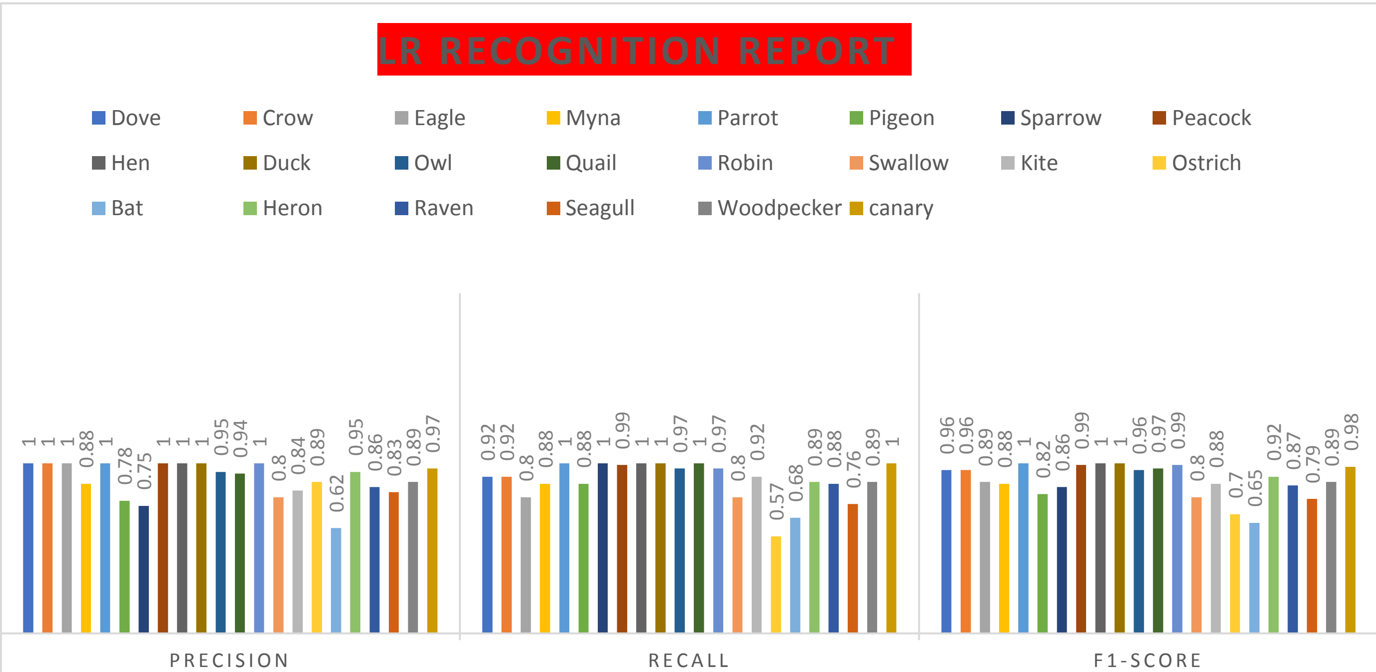
a) SVM Recognition report



b) KNN Recognition report



c) Random forest Recognition report



d) Logistic regression Recognition report

Fig. 3. Performance report of all recognition method.

5. CONCLUSION

We have recognized several types of bird's images and performance analysis of four machine learning algorithms. It is concluded on the basis of experimental results that, SVM get 95% accuracy, KNN get 91% accuracy, RF get 93% accuracy and LR get 90% accuracy. We have observed that SVM performs better results as compared to the other machine learning techniques. The whole process we have used python as the programming language for image recognition. This work has potential to utilize for other recognitions tasks as well as for greater dataset that consists of more classes of birds.

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