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Evaluating the Effectiveness of Machine Learning Techniques for Flower Recognition

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Abstract

Identifying different kinds of flowers and leaves according to their traits is very beneficial in several agricultural and medicinal domains. This article applies machine learning methods to the problem of flower identification using their unique traits. The accuracy of a collection of floral data is determined by using the machine learning techniques Knearest neighbor, Random Forest, and Decision Tree. The Python programming language is used to apply algorithms to a dataset. The KNN machine learning algorithm has the greatest performance when it comes to flower recognition.

Keywords

Decision Tree, Random Forest, K-Nearest Neighbor, Machine Learning, and Flower Identification

I. INTRODUCTION

Machine learning is a kind of artificial intelligence that can discover patterns within data. One kind of artificial intelligence is machine learning, which allows computers to mimic human learning abilities. The machine gains the capacity to learn with the aid of certain computational techniques.

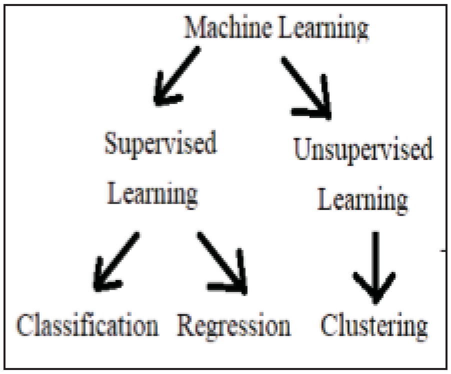

Fig. 1. Types of machine learning algorithms

With ML's assistance, businesses may embrace the automation age and speed up digital innovation in the ever-changing corporate world. Also, some may say that AI/ML is essential for some industries to keep up with the competition, including digital payments, banking fraud detection, or product suggestions. The many types of machine learning algorithms are shown in Figure 1. In supervised learning, we train a computer to recognize patterns in data by feeding it labelled examples. We use the tagged data to teach the machine. When training a computer in unsupervised learning, we do not use labels or classifications. When it comes to machine learning, Reinforcement Learning is by far the most popular. Instead of having predetermined responses, this kind of learning machine lets the agent itself choose how to process the input. It is from instances that the agent learns. it seeks to maximize the benefit of the activity if it is good. If the action is subpar, it will fix it on its own.

II. LITERATURE SURVEY

Automatic flower disease identification using computer vision and object recognition methods of image processing is presented by G. Tigistu and Y. Assabie [1]. In this study, eight different types of floral illnesses are classified. Each floral picture is used to train an artificial neural network using seven input characteristics. After being trained, the model had an average accuracy of 83.3% when it came to detecting illnesses in flowers in photos without labels. For the purpose of distinguishing between healthy and unhealthy flowers, floral textures are used as features to represent photographs. The method for recognizing herb blossoms utilizing characteristics such as the size of the bloom, its RGB color, and the edges of its petals is detailed in paper [3]. The identification method has an average accuracy of 94% and a precision of 98%. The system accesses each picture in less than 0.9 seconds. A method for flower classification using image processing is presented in the article [4]. Image analysis is performed by using the flower's color and edge properties. Edge properties are obtained using the seven-moment algorithm of forms. The RGB and HS characteristics may be discovered using histograms. Flower categorization uses K-nearest neighbor (KNN). The accuracy of this setup is more than 80%. By using color and edge clustering, the authors of the research [7] provide an automated method for flower identification. Color and edge recognition are used to locate flower shapes. Next, classify its color groups and contour shapes using k-means clustering and history matching. The effectiveness of the contour identification is enhanced by combining color and edge contour detection. The algorithm obtains an accuracy of 94.8% after matching the input picture with the tagged photos of 100 flower breeds. The author of article [8] suggests a method for classifying flowers by using a convolutional neural network. It surpasses all prior approaches with an accuracy of 84.02% in categorization. Classifying flowers using this method yields excellent results. This system is suggested as a new convolutional neural network (CNN). The CNNs used by the framework to extract features are effective for many different types of object classification tasks. The author of the aforementioned article [9] investigated the possibilities for precise orchid flower identification and classified them into five distinct visual texture kinds. In this paper, we present a method for object detection using a

Viola-Jones Object Detection System with LBP features and an Adaptive-Boosting (AdaBoost) ML meta-algo. We achieve our targeted accuracy in classification by training a binary-tree of linear SVM classifiers on a set of training data. In order to get a better accuracy score, the authors of the study [12] use a machine learning classifier like Random Decision Forest or Logit Regression. CNN training is a computationally heavy process, and this approach often reduces hardware requirements. A wide variety of ML techniques, including KNN, Logit Regression, Statistical Decision Trees, and Random Decision Forests, are used to train CNN. Using Logit Regression as the dataset's ML classifier, it is verified that the arrangement accurately computes a precision of 97.5%. The effectiveness of machine learning algorithms in identifying flowers based on their properties is examined in this research. Numerous additional scholars [13]–[20] also contribute to this field and provide novel approaches. What follows is an example of the proposed task.

III. PROPOSED WORK

The objective of this study is to assess the performance of ML algorithms in flower identification using their unique traits. The first step in training a machine learning algorithm is selecting a data set to use for training. The machine learning algorithm model is tested on a randomly selected portion of the data set, accounting for 70% of the total. We next test the computer's functionality on the remaining 30% of the data set. There is an air of arrogance in the data selection process for training and testing. We may modify it later on. In Figure 2 we can see the anticipated work flow diagram for evaluating the machine learning algorithm's output. The first stage involves training the machine learning model, which entails feeding it a dataset and then executing the algorithm. The accuracy of the machine learning algorithm is evaluated in the second stage. The final phase involves creating confusion matrices and evaluating the outcomes. Step four involves evaluating the results. Python is used to implement the suggested model. The outcomes of the planned effort are shown in the section that follows.

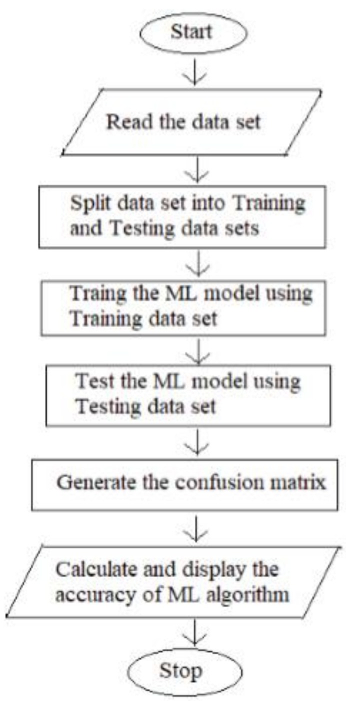

Fig. 2. Proposed model for flower detection using ML

This research delves into the capabilities of artificial intelligence and machine learning in the realm of flower recognition, which is a relatively uncharted territory.

IV. RESULT AND ANALYSIS

Three machine learning algorithms—KNN, decision tree, and random forest—are used to assess the proposed approach. In Figure 3, we can see the KNN machine learning algorithm's confusion matrix. Figure 28 shows that 28 times, KNN guesses zeros at end performance correctly. On twenty-two occasions, it has made sound predictions. Its accuracy ranges from 2 to 23 times.

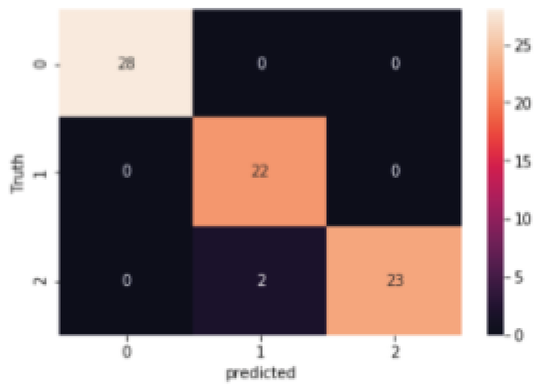

Fig. 3. Confusion matrix for K-nearest neighbor algorithm

You can see the random forest ML algorithm's forecast confusion matrix in Figure 4. As can be seen from the graphic, it provides 26 separate instances of correct zero estimations for ultimate performance. Out of twenty-four attempts, it gets one's right and two times it gets it incorrect. It gets the two's right twenty-two times and gets them wrong once.

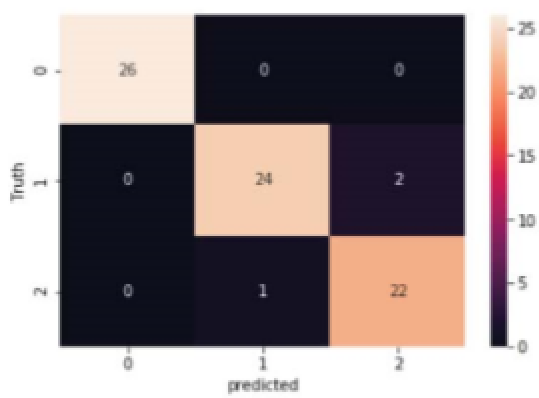

Fig. 4. Confusion matrix for Random Forest algorithm

Figure 5 shows the DT algorithm's uncertainty matrix. In the end result, the estimation of zeros is right twenty-two times. It gets one's right 27 times out of 30, and one's incorrect 5 times. On two to twenty occasions, it gets the forecasts right, and on one to two occasions, it gets them wrong. You can see that the estimate is spot on in Table 1. As a minimum for all three machine learning techniques, the DT's computed consistency is 93.33%. According to most assessments, random forest outperforms decision trees but is 96% less effective than KNN when it comes to making predictions.

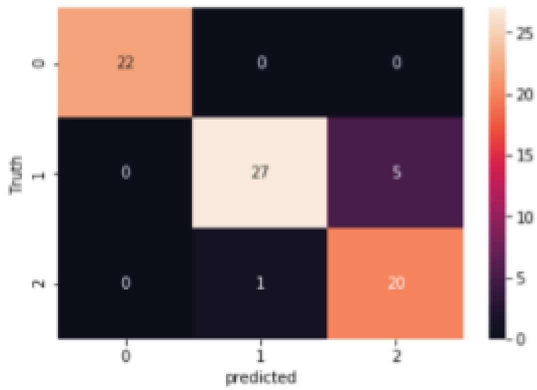

Fig. 5. Confusion matrix for decision tree algorithm

The KNN method outperformed the other two machine learning algorithms with a prediction accuracy of 97.33%. It follows that KNN outperforms decision trees and random forests when it comes to feature-based floral identification. A table comparing the three machine learning techniques' estimate accuracy is shown in Figure-6. The following section illustrates the conclusion and possible breadth of this project.

TABLE I. COMPARISON OF PERFORMANCE

Sr. No	Machine Learning Algorithm	Performance
1	Decision Tree	93.33%
2	Random Forest	96.0%
3	K-Nearest Neighbor	97.33%

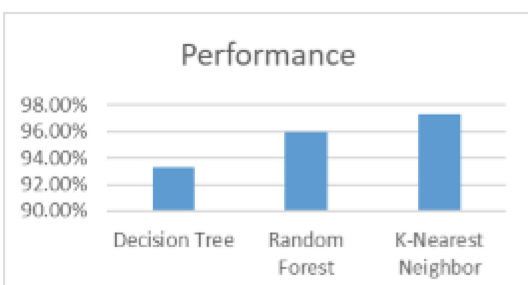

Fig. 6. Prediction Accuracy

V. CONCLUSION AND FUTURE SCOPE

In order to identify flowers based on their traits, this research use ML. New variables are included in the flower dataset, including KNN, random forest, and decision tree. Compared to decision trees and random forest ML techniques, KNN is shown to have a greater prediction accuracy. Eventually, we will also see how well other deep learning systems do at detecting flowers. Other floral data sets may also be used to examine the forecasting performance of these three machine learning techniques. The scope of this study is not exhaustive. You can see how dividing up data for training and testing works.

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