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CLOUD COMPUTING USING MACHINE LEARNING FOR AGRICULTURE APPLICATION

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Abstract: Three types of machine learning were used in this paper: support vector machines (SVM), random forests, and the Naive Bayes. There are four main categorization metrics used to assess the efficiency of the system designed for the identification of insect pests. The four metrics covered here are accuracy, precision, recall, and F1-score. These results demonstrate that our enhanced SVM provides superior performance to the state-of-the-art approaches for automatic pest identification in crops.

Keywords: Machine Learning, Random Forests, SVM, Naive Bayes

I. INTRODUCTION

Farmers face a big obstacle in the form of pest insects that cause harm to their crops. According to the estimations provided by the Food and Agriculture Organization (FAO), these invasive species are to blame for the loss of 20–40% of the world crop each and every year [1. It is estimated that annual losses caused by pest infestation and invading insects amount to a total of $220 billion, which is almost comparable to $70 billion in United States dollars [1].

To achieve this objective, farmers apply a wide variety of pesticides to their crops in order to enhance the quality of their produce and increase the period of time that it is possible to preserve it. On the other hand, exposure to these pesticides for extended periods of time has been connected not only to the destruction of the ecosystem but also to an increased chance of catastrophic illnesses such as cancer, severe respiratory and chromosomal abnormalities, and even stillbirth [2]. As a result of this, the agriculture sector is in desperate need of cutting-edge technical solutions that will enable the early detection of plant pests and a reduction in the inadvertent application of pesticides.

Recently, the concept of smart agriculture was developed to refer to the application of AI strategies, information, and wireless communication technologies, such as the Internet of Things (IoT), in order to achieve precise control over crop diseases, fertilization, irrigation, and plant pests in the agricultural field [3, 4, 5, 6]. This was done in order to realize our objective of achieving what we refer to as precise agriculture. The monitoring of crop health is the most fundamental application of smart agriculture, and it involves conducting an analysis of the condition of the farm in terms of the organisms that are harmful to plants [4]. Because of the intricate architecture of these insects and the high degree to which they resemble one another [7], farmers have a difficult time correctly identifying which insects may be considered pests.

In addition, manual methods for identifying insect pests are labor-intensive, pricey, and fraught with the possibility of making errors. If, on the other hand, farmers are capable of recognizing insect pests at an early stage, they will have a much simpler time putting a stop to the spread of insect pests by employing the necessary insecticides [7]. Previous research has concentrated primarily on the application of computer vision systems and image processing through the use of artificial intelligence techniques such as machine learning and artificial neural networks in an effort to find answers to the challenges that are currently faced in the agricultural industry.

Entomologists have pushed for the use of image recognition to detect insect pests for a variety of objectives, including the computation of a biodiversity index based on the number of various types of insects [8]. Image recognition can be used to identify insect pests in a variety of settings. Recently, deep learning methods such as convolutional neural networks (CNNs) have been utilized in agriculture as a viable solution for autonomous classification of agricultural pests [9], [10], and [11].

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Since CNNs work on raw pixel data and generate their own feature generators, they are ideally suited for more traditional methods of image processing and machine learning. In addition, CNNs have shown that they are able to withstand picture noise and illumination variation in a wide variety of applications, including medical image analysis [12, 13], mechanical intelligent defect identification [14], and infrastructure crack detection [15].

II. RELATED WORKS

The following is a list of some of the many research that have been done in the past that have shown image-based systems that make use of several CNN architectures for the autonomous, deep learning-based categorization of crop pests: For the goal of in-depth residual learning, [11] ten distinct categories of insect problem pictures have been presented, each of which depicts an insect problem in an agricultural scenario that is singular to itself. Its accuracy was around 98.0% better than that of the support vector machine, as well as that of the typical BP neural networks. The Region Network was proposed [17] as a means of locating pests in photos and completing the categorization process with the assistance of CNNs.

In [18] developed a fine-tuned GoogLeNet model within a framework of deep learning-based pest identification in order to classify 10 distinct types of crop pests making use of a dataset that was manually collected. This was done in order to accomplish their goal of identifying the pests. This was done in order to categorize the undesirable organisms. As a product, you will have achieved a detection rate of pests that is greater than 98%. The process of training this model consumes a substantial chunk of time and calls for a sizeable portion of the available processing power of the computer. Certain deep learning models, such as Inception-V3, posed a challenging problem when applied to the data set that was under investigation. This offered a significant obstacle.

As in [9], a saliency-based approach was combined with convolutional neural networks (CNNs) in order to produce a system for the recognition of insects. This approach was used to create the system. Both a tiny dataset and the massive IP102 dataset were used to examine the performance of the algorithm [19], with the former yielding an accuracy rate of 92.43% and the latter producing a rate of 61.93%. The technique that was suggested, on the other hand, does not perform particularly well when applied to images of pests that have a large degree of variability within the same category.

Deep convolutional neural networks (CNNs) and transfer learning were proposed for the categorization of agricultural pests [7], and they were evaluated on three bug datasets that were made available to the public. There were between 24 and 40 different picture classes of crop-eating insects included in these databases. Their accuracy in categorizing was noticeably higher than that of deep learning models that had already been pre-trained by researchers from other institutions. It has been postulated [10] that one can use deep residual networks to classify primary and secondary pests in RGB imagery of cotton fields. The accuracy of 98.0% that was achieved was higher than that of any of the preceding CNN models that had been developed.

A self-learning saliency feature map-based deep learning pipeline was also constructed [20] in order to automatically detect and count agricultural pests present in photos. This was done in order to save time. A comparative study [21] was conducted on the detection and identification of tomato plant pests in greenhouses, and both machine learning and deep learning were put through their paces in the context of the study. When it comes to effectively identifying tomato pests, our research has proved that deep learning solutions perform much better than the standard machine learning approaches. In order to classify insect pests using the publicly available IP102 dataset [22] compared a CNN model to four different machine learning techniques. The goal of this comparison was to determine which machine learning technique would provide the most accurate classification of insect pests. This comparison was conducted with the goal of determining which approach to machine learning would be most successful in the categorization of insect pests. The CNN model that was developed was successful in achieving the highest possible classification rates, which were 91.5% and 90%, respectively, for the nine and twenty-four different kinds of crop pests. It has been suggested that farmers could benefit from the application of transfer learning models to aid in the control of pests in soybean fields by making use of aerial imagery captured by high-resolution drone cameras. This imagery would be taken from above the field.

III. PROPOSED METHOD

All of the information that is relevant to soil is compiled and kept in a single place on the cloud, making it simple to retrieve when necessary. In addition, the information concerning the weather patterns of the area is saved in the cloud so that it can be protected from prying eyes at all times. This cloud service offers a number of different machine learning methods accessible to users, some of which include naive bayes, support vector machines, and random forests, amongst others.

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Data on the climate and the soil are fed into machine learning algorithms so that they can determine how much information should be collected on a particular crop. After then, the outcomes of this procedure are made accessible to subscribers through the use of mobile applications. Users who have registered for the service will have access to the forecasts generated by machine learning. The user will have the ability to make adjustments to the levels of humidity and wetness once they have registered their account.

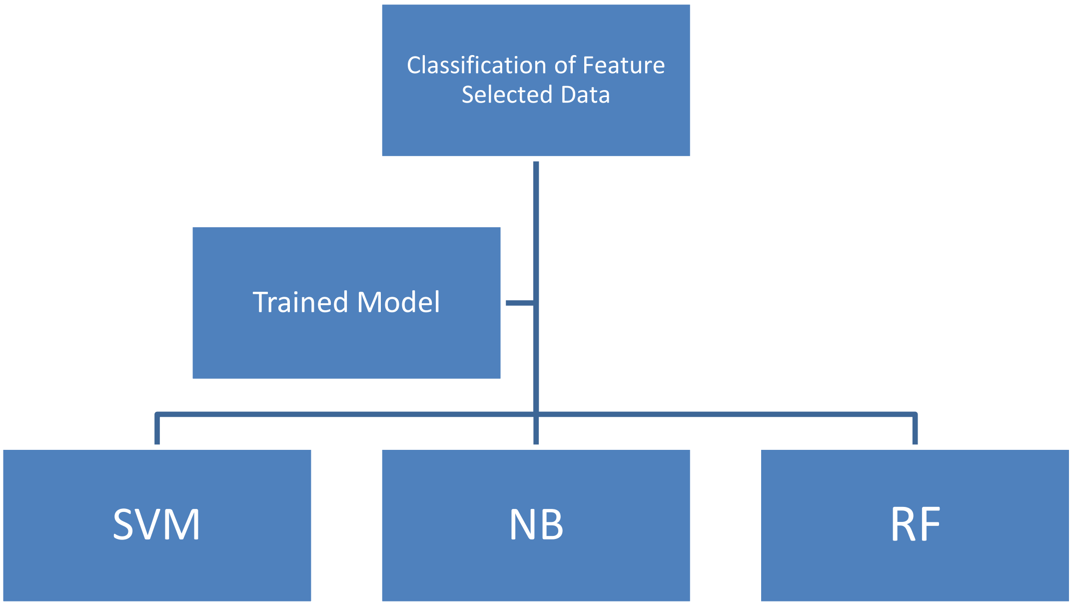

Figure 1: Proposed Method

Support Vector Machine

The algorithms that are used in machine learning, such as those that are used by support vector machines, are able to use data to increase their capacity to recognize patterns and make predictions about new scenarios. One example of an algorithm that is used in machine learning is one that is used by support vector machines. SVM models make an effort to optimize the distance between the various classes so that incoming samples can be classified according to which side of the gap they fall on. This allows for the maximum amount of fresh water to be saved through the use of smart irrigation, which in turn maximizes the amount of money that can be saved.

Random Forests

The powerful ensemble learning method known as random forest is frequently utilized by applications that require categorization and demand for its utilization. During training, it creates a thicket of decision trees, the classification of which is the key mechanism for establishing the outcomes that are intended to result from the training. By generating decision trees from random subsets of the training data, random forests are able to improve model performance while simultaneously reducing the risk of overfitting. These decision trees were generated using a method that involved random forests.

Naïve Bayes

Naïve Bayes, a probabilistic classifier that is founded on Baye theorem, employs the utilization of independent characteristics. It is presumable that the existence of an increased number of features in a test case will result in an increased likelihood that the instance in question is a member of a specific class.

User interface module

A User Interface (UI) that has been developed for smartphones on any platform, such as Android-based or iOS devices, makes it simple for a farmer to identify a crop pest in either an open field or a greenhouse environment. This is the case whether the farmer is using the smartphone in a field setting or in a greenhouse setting. If a user takes an image of a bug that they are unable to identify, the interface will send the image along with an HTTP POST request.

The flask web is in charge of managing all of the queries, as well as storing the input images in the cloud before sending them on to the deep learning module. Additionally, it is responsible for communicating the photographs to the module.

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When the image-based recognition process is complete, the user interface that was developed to guide farmers through standard agricultural procedures will present the findings of the category of pests and the chemicals that are relevant to those pests. This will happen after the image-based recognition procedure has been completed.

IV. RESULTS AND DISCUSSIONS

A data collection consisting of 330 soil recordings was compiled in order to make it easier to carry out the experimental study. It is possible to ascertain the level of moisture and humidity that is present in the soil for specific crops at specific sites. In addition, the package of information included information that pertained to the weather conditions in the area. In this particular experiment, three different approaches to machine learning were utilized: support vector machines (SVM), random forests, and the Naive Bayes method.

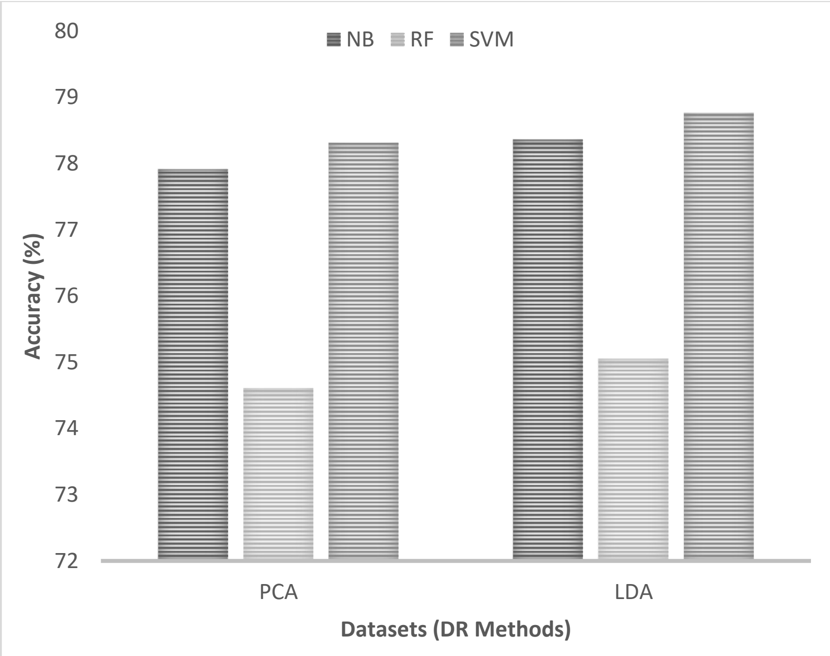

Figure 2: Accuracy

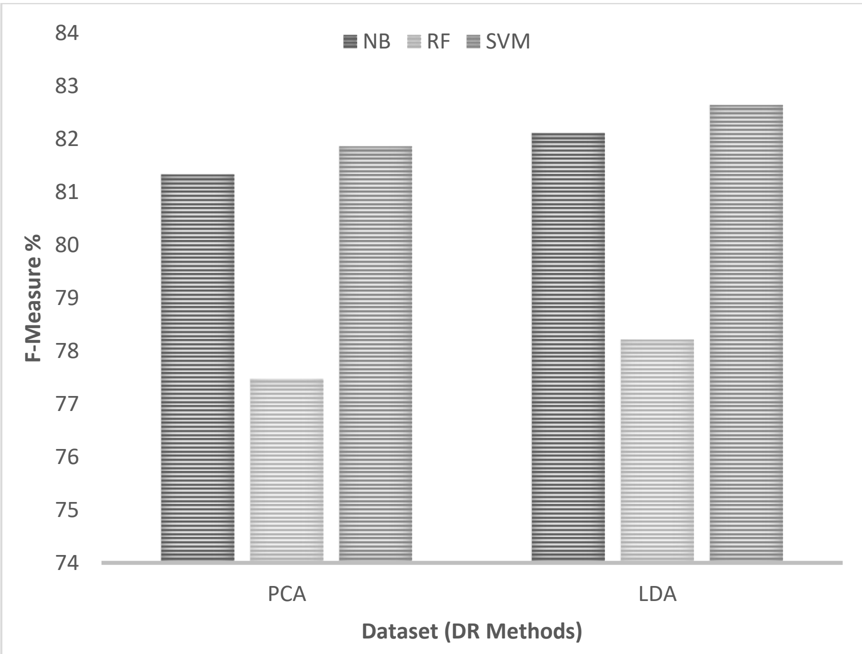

Figure 3: F-Measure

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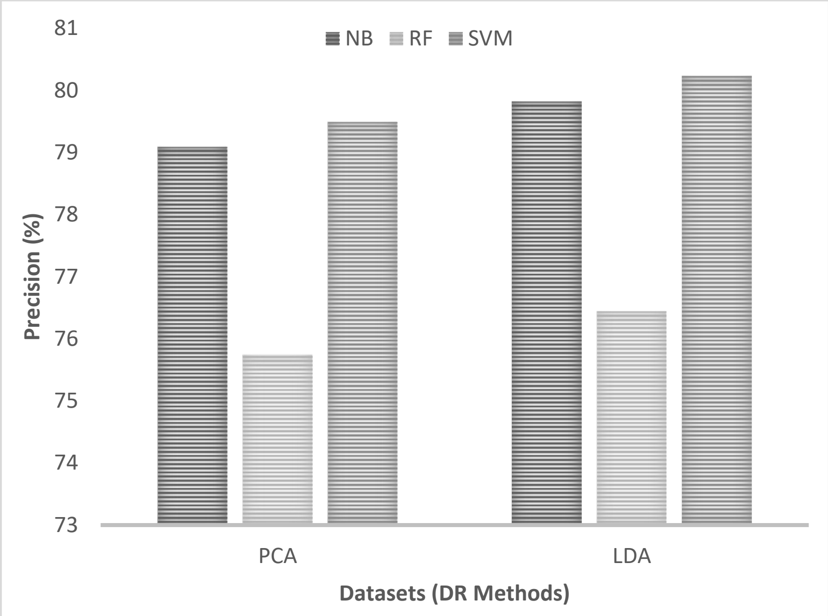

Figure 4: Precision

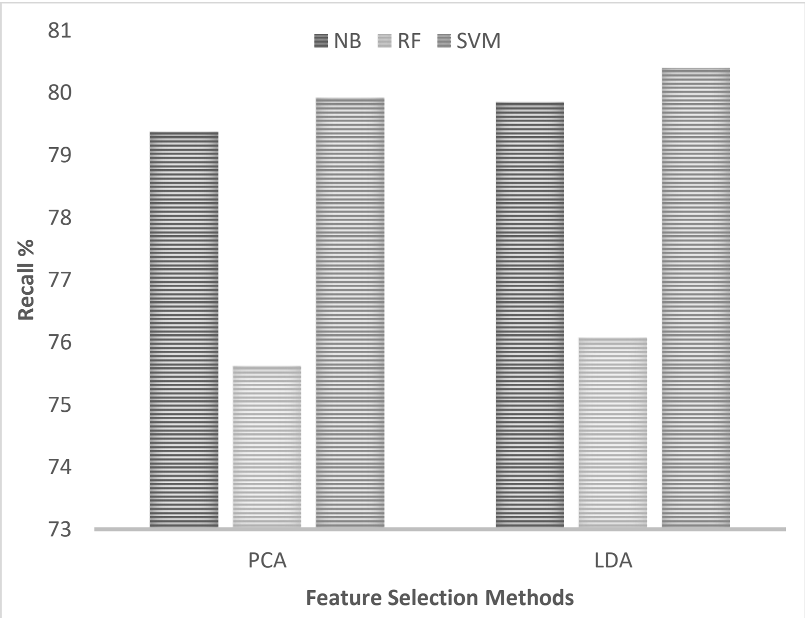

Figure 5: Recall

There are four primary classification metrics that are utilized in the evaluation of the overall performance of the system that was developed for the recognition of insect pests. Accuracy, precision, recall, and F1-score are the four measures that are included here.

A comparison of the efficacy of the resultant method of pest categorization to that of other methods that were utilized in an earlier investigation can also be shown in Figure 2-5. These other approaches were used in the first study.

Because of these findings, it is clear that the performance of our improved R-CNN for automatic pest identification in crops is superior to that of the methods that are currently being utilized. When it comes to finding red spider mites, the BP neural networks method does an acceptable job of recognizing aphids, but it is absolutely useless for doing so.

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V. CONCLUSIONS

In this paper, immediate action be taken in order to put technological solutions into place, such as intelligent irrigation systems, in order to improve the effectiveness of irrigation in the production of agricultural goods. However, in order to achieve the level of accuracy that is desired, the efficacy of such a system is dependent on soil data as well as climate data that is particular to that region. Both of these types of data are region-specific.

An innovative irrigation system that was designed with cloud computing and the Internet of Things in mind is examined in this article. In this particular system, machine learning algorithms were utilized to make forecasts regarding the quantity of potable water that would be required for the cultivation of a variety of different crops in order to achieve a high level of success. Because of this, there is a sizeable drop in the amount of water utilized. Because of the implementation of smart irrigation, there is going to be a significant shift in the paradigm that governs the agricultural industry.

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