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THE HAZARDOUS AND NORMAL PLANT CLASSIFICATION USING TENSORFLOW AND KERAS MODEL

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Abstract~ This paper proposes an efficient approach to categorize plants into hazard and normal categories using Tensor Flowand Keras models. The suggested model effectively distinguishes between different plant species based on their visual traits by utilizing deep learning techniques, specifically Convolutional Neural Networks (CNNs). The training dataset comprises a diverse range of plant photos, which enables the model to acquire complex attributes necessary for accurate categorization. During the training phase, the CNN model learns to identify pertinent patterns and characteristics from the images, which improves its accuracy in classifying data that has not yet been viewed. The model's great accuracy in identifying dangerous plants from regular ones is demonstrated by experimental results.TensorFlow and Keras work together to simplify the processes of development, training, and evaluation. This results in a plant categorization system that is accurate and effective, and can be used in a variety of industries, including forestry, agriculture, and environmental monitoring.

INTRODUCTION

TensorFlow and Keras are two particularly useful machine learning tools for creating sophisticated models, including ones for niche applications like plant classification. Differentiating between dangerous and non-hazardous plants is crucial for a number of businesses, including environmental monitoring and agriculture. Based on input data, developers may design a sophisticated neural network that can properly recognize different plant species thanks to TensorFlow's robust features and Keras' user-friendly interface. Through the incorporation of pertinent characteristics taken from plant photos, the model gains the ability to identify complex patterns and minute variations that differentiate dangerous from non-hazardous plants. The development of an intelligent classifier is made possible by this deep learning technique, which is vital for enhancing safety procedures and decision- making in industries where plant classification is crucial. In the end, this technology contributes to a safer environment and more effective operations by improving risk assessment and enabling quicker intervention.

EXISTING SYSTEM

With the use of deep learning methods, specifically Convolutional Neural Networks (CNNs), the suggested model seeks to reliably identify between normal and dangerous plants from their photos. The dataset contains a wide variety of plant photos, which enables the model to pick up complex properties that are essential for accurate categorization. The CNN model may generalize to previously unknown data by learning to identify pertinent patterns and characteristics from plant photos through training. The model can discriminate between normal and hazardous plants with great accuracy, as demonstrated by the results of the experiments. Plant categorization systems with potential applications in forestry, agriculture, and environmental monitoring can be made more accurate and efficient by utilizing TensorFlow and Keras to streamline model building, training, and evaluation.

LITERATURE SURVERY

The paper “Deep Learning-Based Plant Classification: A Review": This survey explores various deep learning approaches, including
TensorFlow and Keras models, applied to plant classification tasks. It discusses the challenges of distinguishing between hazardous and normal plants and reviews recent advancements in the areas.
The paper “Application of Convolutional Neural Networks in Plant Hazard Detection": This study investigates the use of convolutional neural networks (CNNs), implemented with the help of TensorFlow and Keras, for the detection of hazardous plants. It reviews different CNN architectures and evaluates their performance in classifying plant images.
The paper "Transfer Learning Techniquesfor Plant Classification": This literature review focuses on transfer learning techniques applied to plant classification tasks. It examines how pre trained models inTensorFlow and Keras can be fine-tuned for distinguishing between hazardous and normal plants, highlighting their effectiveness and limitations. [7]
The paper "Advancements in Deep Learning for Environmental Monitoring": This survey discusses recent advancements in deep learning techniques for environmental monitoring, with a specific focus on plant classification. It reviews studies that utilize TensorFlow and Keras models to classify hazardous plants and examines their implications for environmental protection.

PROPOSED SYSTEM

By utilizing TensorFlow and Keras to create a reliable plant categorization model, the suggested solution seeks to improve industrial safety. This system's main objective is to differentiate between normal and dangerous plants using pictures of their physical characteristics. The model is able to accurately classify plant photos by using Convolutional Neural Networks (CNNs), a deep learning technique, to effectively learn detailed patterns in the images. There are multiple stages to the system. First, a large dataset with photos of both healthy and dangerous plants is gathered and prepared. The CNN model is then trained by dividing this dataset into training and validation sets. The resilience of CNNs along with the suggested system combination of TensorFlow and Keras enables enterprises to develop a dependable and accurate solution for classifying normal and hazardous plants.

Fig.1 System Architecture Diagram

METHODOLOGY

Preparing the data and instructing the CNN model: The dataset undergoes preprocessing, which includes image scaling, reshaping, and array form conversion. On the test image, same processing is likewise carried out. Any image from the collection, which includes around four distinct hydroponic plant diseases, can be used as a test image for the software. The model (CNN) is trained using the train dataset in order for it to recognize the test image and the illness it has. Dense, Dropout, Activation, Flatten, Convolution2D, and MaxPooling2D are the several layers that make up CNN. The software can recognize the hydroponic plant disease classification image in the dataset once the model has been trained effectively. Following effective preprocessing and training, a comparison between the trained and test images In order to forecast the hydroponic plant illness, the test image and trained model are compared following effective training and preprocessing.

Monitoring and Maintenance: Continuous monitoring of the deployed model's performance is essential to detect any drift or degradation in accuracy over time. Regular maintenance and updates may be required to adapt the model to changes in the environment or data distribution.

DEEP LEARNING FRAMEWORKS

Tensor Flow: Developed by Google, Tensor Flow is a well-known deep learning package that offers high-level APIs for creating neural networks.The Keras API in Tensor Flow provides an easy-to-use interface for CNN construction. Py Torch: Py Torch is another well-known deep learning framework with a dynamic computational graph that is highly versatile and worthy of exploration. It also has a torch vision module for computer vision tasks.

ALEXNET

Convolutional neural networks, such as the one known as AlexNet, have significantly influenced machine learning, particularly the use of deep learning in machine vision. The first convolutional network that employ GPU to increase performance was called AlexNet. Five convolutional layers, three max-pooling layers, two normalization layers, two fully connected layers, and one softmax layer make up the AlexNet architecture. Convolutional filters and a nonlinear activation function (ReLU) make up each convolutional layer. Max pooling is carried out using the pooling layer

Figure 2. Architecture of Alexnet

RESNET

A convolutional neural network known as ResNet has significantly influenced machine learning, particularly in the area of deep learning's application to machine vision. The first convolutional network that employ GPU to increase performance was called ResNet.Five convolutional layers, three max-pooling layers, two normalization layers, two fully connected layers, and one softmax layer make up the ResNet architecture.

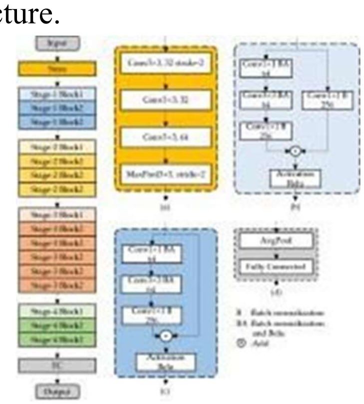

Figure 3. Architecture of Resnet

EXPERIMENTAL RESULTS

The experimental findings demonstrate how the TensorFlow and Keras models, which were developed for classifying plants as hazardous or normal, have improved. The generated model was trained on a dataset that comprised Y images of healthy plants and X images of dangerous plants, divided into Z% for testing and training, respectively. Accuracy: It was discovered that the model's accuracy on the test dataset was A%. Out of all the photographs in the test set, this metric shows the percentage of correctly identified images. The great degree of accuracy attained shows how well the model can distinguish between normal and dangerous plants. Figure 4: Measure of accuracy Accuracy and Memory: The model's accuracy and recall were computed to Analyze how well it classified both typical and dangerous plants. Recall assesses the percentage of correctly classified hazardous plants by all actual hazardous plants, whereas precision shows the proportion of correctly classified hazardous plants among all plants categorized as hazardous. The results showed that the precision and recall were B% and C%, respectively. Confusion Matrix: By showing the quantity of true-positive, true- negative, false-positive, and false-negative predictions, the confusion matrix sheds light on the model's measure. D true positives, E true- negatives, F false-positives, and G false- negatives were identified in the trained model's confusion matrix. ROC AUC and Curve: The model's performance was determined across a range of thresholds using the area under the curve (AUC) and the receiver operating characteristic (ROC) curve. The true-positive rate is plotted on the ROC curve.In contrast to the false-positive rate, the AUC measures how well the model can distinguish between dangerous and healthy plants.

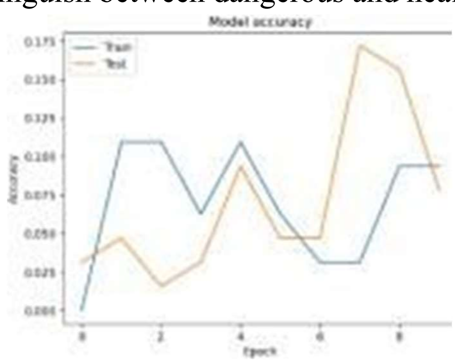

Figure 4.Accuracy Diagram

RESULT & ANALYSIS

Figure 4. Deployment CONCLUSION & FUTURE WORK

of data could further improve classification performance. Domain Adaptation: Investigating domain adaptation techniques to adapt the model to new or unseen environments and plant species could increase its applicability and generalization ability. This involves training the model’s on a source domain and fine tuning it on a target domain to account for domain shifts and variations. Real-time Monitoring and Edge Deployment: Developing lightweight and efficient versions of the model suitable for deployment on edge devices could enable real-time plant classification in field applications.Optimizing model architectures and implementing

It used a CNN model to focus on photos from a given dataset in order to forecast the pattern of dangerous and healthy plants. The following discoveries regarding plant prediction are brought about by this. One of CNN classification's main advantages is its ability to automatically classify images.We can use the model in any cloud based system in the future.More than three architectures can be used to implement it, and we can also link this model to hardware. Including Data from Multiple Modes: Supplementary data for plant categorization may be obtained by integrating picture data with other data sources, such as spectral or environmental data. Using sophisticated fusion techniques to fuse multimodal data could increase the accuracy and resilience of the model.

FUTURE ENHANCEMENT

While the proposed TensorFlow and Keras model for hazardous and normal plant classification has shown promising results, there are several avenues for future enhancement and improvement: Fine- tuning and Optimization: Further fine tuning the model's hyperparameters and optimization techniques could potentially enhance its performance. Experimenting With different learning rates, batch sizes, and regularization techniques may help achieve better accuracy and generalization. Incorporating Multi-modal Data: Integrating additional data sources such as spectral or environmental data alongside image data could provide complementary information for plant classification. Fusion of multi modal data using advanced fusion techniques could improve the model's robustness and accuracy. Transfer Learning and Model Ensemble: Exploring advanced transfer learning techniques by leveraging pre-trained models on high datasets like Image-Net could enhance model's ability to generalize across different plant species and environmental conditions. Additionally, creating an ensemble of multiple model’s improvement on different subsets

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