DETECTION OF RICE LEAF DISEASES BY USING CNN

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ABSTRACT

The present research concentrated on spontaneous recognition approach for image exploration on rice leaves in a variety of usual conditions for advance investigation. The condition plays a crucial role in regulating and eradicating of features in image processing. Some of the dangers, nevertheless, continue to be inaccurate at forecasting inflammation. The anticipated algorithm concentrates on a precise challenge to predict the inflammation from the early warning in order to counteract such hazards. In rice crops, microbial leaf blight and brown spot are the two most common bacterial and fungal inflammations; they lead to harvest loss and worse grain quality. An automatic detection approach for pinpointing the precise inflammation in rice leaves under various natural conditions has been proposed after analyzing several hybrid image analysis and regulation algorithm techniques. Using image data, this structure can categorize the proportion of diseased and vigorous rice plants. With a large agricultural farm, this approach can simplify our task of identifying diseased plants. I'm optimistic that it will expedite the process of classifying our work.

Keywords : Disease Detection, ML, Rice Leaf, Supervised Algorithms

INTRODUCTION

A crucial factor in examining bogus insights and in-depth learning is the picture classifier. This constitutes the most frequently used skills and exploration topics to address concerns with livelihood challenges and realities. Organizations deal with a variety of problems every day that can be properly handled and understood by employing synthetic perspectives and algorithms. Recognizing whether the organic item is virtuous, which food is good for our healthiness or horrible in fact, prepared to find which disease the raw material was affected by, as well as whether one should eat it or not, were problems like this. It determines which organic goods are excellent and which are overpriced in order to fix this problem. I'm going to employ CNN searches, relapsing computations, and false discoveries and methods to figure out which Apple natural item is genuine and which one is ruined. In a mega store, organic goods are frequently not brand-new, but because of the environment, they are prepared to sale. Anyone may use this model to comprehend that by fairly screening organic goods, it will be advantageous for them to save cash instead of acquiring novel organic goods from retail stores.

In 2019 [1], the agricultural industry contributed to Bangladesh's highest GDP, BDT 10.73 billion. The production of rice accounts for half of the agricultural GDP. As a result, this also accounts for nearly 50% (48%) of rural employment [2]. Rice aids as a primary nourishment for the majority of people for two-thirds of the recommended regular calorie consumption per person, while also playing a significant role in the economics of the nation. According to the USDA, the total harvest of rice will be 11 million hectares and 35.3 million pounds in 2019-2020, respectively [3]. The financial outcomes demonstrate Bangladesh's vital emphasis on efficient harvesting of rice. A dominant factor in guaranteeing sustained growth in the economy and maintaining the targets set would be disease-free rice cultivation.

Bangladesh must also aim towards industrial breakthroughs that will include smart schemes that can make selections without human contact. In order to achieve this, we developed a computerized system employing machine learning techniques. This system will aid in the development of the nation's agriculture by instantly recognizing and categorizing ailments from photographs of wheat plants.

A survey carried out in Bangladesh between 1979 and 1981 originate 20 rice illnesses, were 13 identified as substantial ones [4]. Back then, brown spot and rice blast were thought to be the furthermost common ailments, but today, brown patch and microbial disfigurement are thought to be the most common and harmful [5]. The exposure of all three rice leaf bugs has been the main emphasis of this research. The fact that these three diseases are common in Bangladesh is the reason.

The designs and forms of these three distinct ailments are idiosyncratic. The ensuing is a portrayal and graphic of the disease physiognomies [6]. Rice leaf blast blades of foliage with tiny extended blemishes at the tips of leaves and edges that develop white to yellow and finally grey as a result of fungal attack have been identified as bacterial blisters.

1.1 Plant Diseases on Rice Crop

Numerous farmers raise rice as their primary crop, and it is typically grown in two seasons: rabbi and Karif. Production for a season takes six months. Diseases are harming the crop as a result of environmental changes, reducing output. The primary paddy illnesses are listed here.

1.1.1 Bacterial Leaf Blight

One of the most dangerous illnesses that can affect rice is bacterial blight. The yield loss increases with the onset of the disease. When vulnerable types are grown in conditions conducive to the illness, yield loss from bacterial blight can reach 70%. Microbial blight has no impact on production when plants are infected at the booting stage, but it does cause poor grain quality and a high percentage of damaged kernels.

Hurricanes and prolonged flooding frequently cause it, which makes it easy for the pathogenic microbes to propagate through bubbling drops on wounds of afflicted plants.

Fig 1.1.1: Bacterial Leaf Blight

1.1.2 Rice Leaf Blast

The fungus Magnaporthe oryzae is the cause of the blast. A rice plant's leaves, cuffs, nodes, head, size, and infrequently the leaf cover are all vulnerable to it. Anywhere blast spores are present, they can cause a blast. It also happens in places where there is little soil moisture, a lot of rain, and cool daytime temperatures. Substantial day-night temperature variations that result in dew deposition on plants while typically cooler temperatures in highland rice favor the growth of the disease. All growing phases of rice can have a blast. However, as plants mature and build up mature crop immunity to the illness, the incidence of leaf blasts tends to decline.

Fig 1.1.2: Rice Leaf Blast

1.1.3 Brown spot

One of the most prevalent and destructive rice diseases, brown spot, has previously received little attention. A fungus called brown spot affects the leaves, sheaths, spike limbs, and spikelet's. The large blotches on the greeneries that can kill the whole leaf and causes noticeable harm. Brown spots can appear at any stage of the crop's growth, though the infection can be most harmful at peak cultivation and the crop's growth phases.

Fig 1.1.3: Brown Spot disease

LITERATURE SURVEY

The pathology of photos is correctly determined using a variety of techniques. While the majority of them employ basic image processing techniques like SVM classifiers, K-means clustering, etc., these are not receiving a lot of focus. Several investigators have recently tackled this topic using a ground-based approach. When it comes to picture recognition, deep neural networks outperform conventional methods by a considerable margin. Dedicated to automatically capturing or analyzing rice diseases in paper [1]. In the field of ML and pattern acknowledgment, DL is a prominent research topic. These issues can be successfully solved in plant pathology, and for vascular disease, they promote an alternative approach based on CNN technology. CNN received training to recognize 10 common illnesses employing more than 500 shots obtained from the pink area's stems and samples. The suggested CNN model obtains 95.48% efficiency while using the single-track correction technique. This perspective outperforms the standard learning model by a wide margin. The results of the assessment of the rice price index demonstrate the likelihood or utility of this process.

In paper [2], The art of technical illustration has evolved to include deep learning. The landscape of the many diseases accessible through the solicitation is the primary problem that arises while utilizing this screening tool. The ion-augmentation technique lessens effects of this issue, and can't replicate a lot of the genuine differentiation. In contrast to studying the entire leaf afterward, this article looks at the usage of single-stranded lesions in this work because of its own distinct traits and organizes more photos to boost data adaptation. It permits the recognition of numerous illnesses that effect the same leaf. Though, there is still a need to disperse possible signs in a way that precludes full automation. In comparison to the level of detail employed in the initial picture, this procedure's accuracy is typically 12% greater. The techniques offered in this research not only intensification the dimension of the presently accessible shots however nevertheless rise the amount of facts since they do not take into consideration the natural variations of every shot. Although this approach has major drawbacks as well, in the setting of limited data, it clearly produces precise outcomes.

Anthracnose-related illnesses and other symptoms are effectively described in paper [3] in this article. Computer vision and deep learning have full-fledged in prominence in current years as a consequence the augmented usage methodologies and procedures for categorizing different illnesses. In order to categorize blue leaves that have cervical disease infection, CNN has been suggested. The following article has been updated with accurate information and a picture of a blue tree from Vaishno Devi's University, India. Kate has images of both healthy and ill leaves on her list. The outcomes indicate that the suggested CNN model has superior accuracy and greater categorization abilities when compared to the alternative method.

In order to provide disease management measures the paper[4] shows that to enhance the quality and quantity of their output, identifying plant diseases is vital. Because they make vast farms more difficult to regulate, respiratory illnesses are highly helpful. Since leaflets are an excellent basis of essential nutrients for undergrowth, it is critical to quickly and precisely recognize leaf diseases. This research contains a technique that can recognize the leaf pathogens of several kinds of blue plants. Anthracnose, Alternaria leaf spots, Leaf Gall, Leaf Webber, and Mango Leaf Burn are five distinct ailments. A database containing 1200 photos of healthy and infected peaches was used to make the identification. The proposed CNN model responds to the diagnostic 96.67% of the time and shows leaf diseases, demonstrating the capabilities to apply in real time.

Using manual criteria extracted from obtained photos to determine the type of infection, the classic disease detection method is utilized in the paper [5]. Additionally, the manner in which these duties are performed entirely relies on the type of manual labor chosen. Through a CNN computerized study, it may be seen. In this study, two different approaches for identifying tomato leaf virus infections are proposed. Twelve courses are used in the initial design to acquire crucial material. The attraction process is applied to enduring vast network in the next design. Data from the Horticultural Village, which comprised three diseases—original decay, flame initiatives, and butterflies—was used for the experiment. The suggested approach makes use of extraction mechanics, a capability CNN has acquired through multiple procedures and achieved broad exactness of 98%.

PROPOSED WORK

The study's primary objective was to gather a sizable dataset of field-captured photographs of rice leaf disease before classifying the images into two groups: bacterial spot images and healthy images. Figure 1.6 depicts a high-level perspective of the proposed system architecture for identifying and categorizing rice leaf diseases.

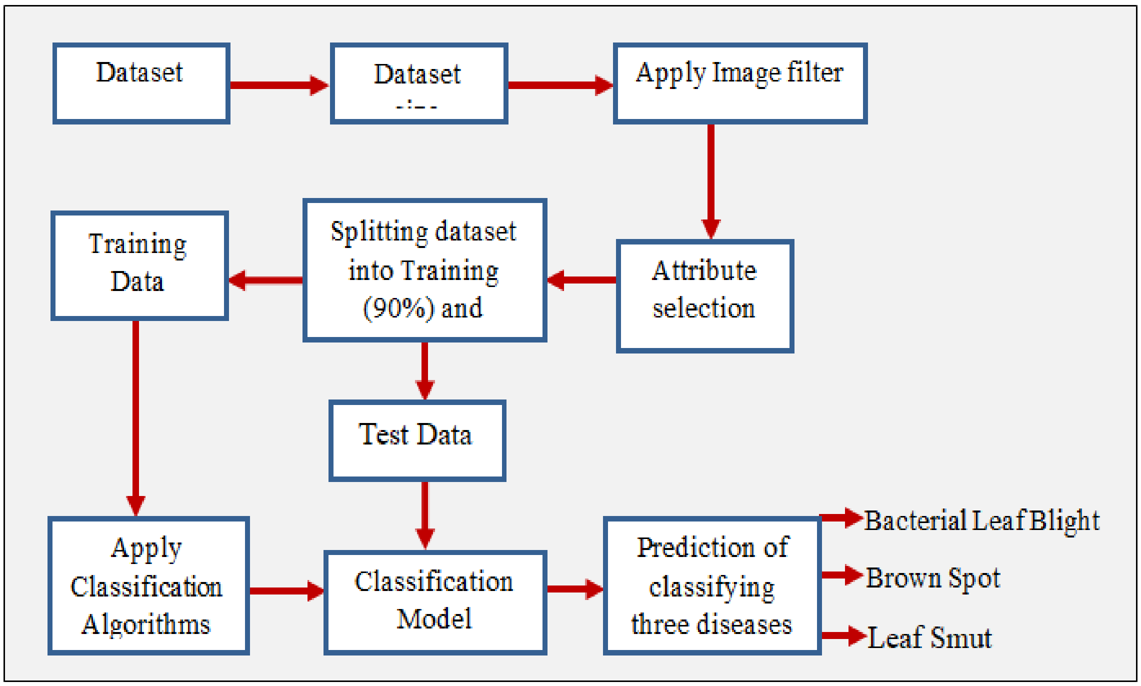

Fig 1.6.1: Block Diagram of Proposed System

The full work cycle is shown in Fig. 1.6 above. By manually classifying affected leaves into three distinct disease categories, the dataset was produced. The ailments caused by bacteria such as leaf blight, brown spot, and leaf smut each have 40 visuals, and there are three of each. Each image is in the jpg file extension. The size of the database was boosted to 400 by enhancing the image quality. Using colour Trend Sort visual screening, the images were subsequently turned into attributes, giving 35 more characteristics to the set. Correlation-based choice of attributes was the technique used to choose notable traits, and it contains 90% of the facts while the remaining 10% are for the test set.

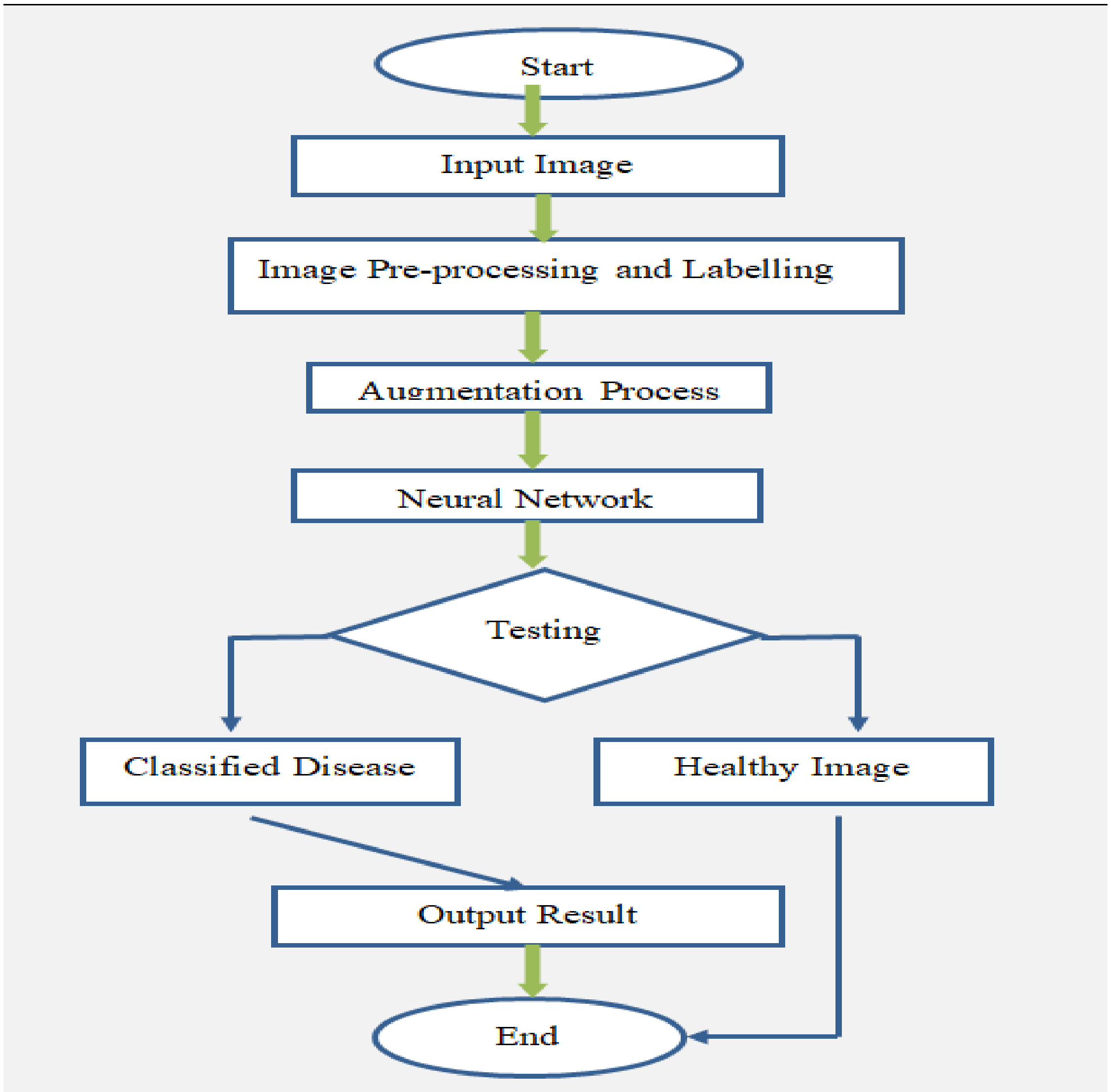

Fig 1.6.2: Flowchart of Proposed System

The systems suggested flowchart displays

Dataset: The types of rice leaf illnesses are utilized as features, and the acronyms of the infections are used as tags, in this information set of the crop leaf diseases.

Pre-processing: During data from training, any picture is resized and shrunk in size to 224 x 224.

Split data: The data set is separated into training and test datasets, or testing and validation datasets.

Initialize Model: At this stage, the learned characteristics and tags are fitted to the method and the CNN model is uploaded to the framework.

Prediction: To make a prediction, a user submits information on rice illness to a website application and then verifies the outcome using a model.

RESULTS

This study provides a better VGG model that leverages DL CNN model-based target recognition as well as placement techniques. This model uses a pre-trained version of the VGG-19 network. By fine-tuning the transfer learning method, the variables of the model that was previously trained improve the predictive characteristics of the CNN layer to tackle the issue of classification of rice leaf disease detection. The majority of the variables in VGG-19 are split among three FC levels. Each of the three fully connected layers of VGG-19 ought to be replaced with one Flatten layer and two entirely linked layers. The convolution layer cannot be linked straight to the thick fully linked layer, thus a flattened layer is added instead. A 2-label Soft max classifier replaces the initial network prep framework in the enhanced edition. Using mainly the fine-tuning transfer learning to fit a detection model with high precision, the soft max classification layer, limited features by abandonment, and max pooling.

The main operation process is as follows:

(1) These are some illustrations of rice sickness. As a trial, the images are taken out of the folder.

(2) The input image is consistent to resolve 224 * 224 in order to increase training effectiveness.

(3) The 3FC layers are enhanced as 1flattened layer and 2FC layers with fewer limitations using VGG-19 Net model. A 2-label Soft max classifier should be used in place of the original model's Soft max classification layer.

(4) The technique of transfer learning was used to optimize the parameters of the detection algorithm using convolution-based and combining layers of the VGG pre-trained model.

(5) It is necessary to use an arbitrary technique and set the momentum limits, the precision standard in order to train and enhance the limits of the 2 FC layers and Soft max layers.

(6) To test the exemplary outcome, extract the data from the input image photographs in the data set.

```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         [(None, 224, 224, 3)]     0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 224, 224, 64)      1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 224, 224, 64)      36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 112, 112, 64)      0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 112, 112, 128)     73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 112, 112, 128)     147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 56, 56, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 56, 56, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_conv4 (Conv2D)        (None, 56, 56, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 28, 28, 256)       0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 28, 28, 512)       1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_conv4 (Conv2D)        (None, 28, 28, 512)       2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 14, 14, 512)       0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv2 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_conv4 (Conv2D)        (None, 14, 14, 512)       2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 7, 7, 512)         0
_________________________________________________________________
flatten (Flatten)            (None, 25088)             0
_________________________________________________________________
dense (Dense)                (None, 3)                 75267
=================================================================
Total params: 20,099,651
Trainable params: 75,267
Non-trainable params: 20,024,384
```

Fig 7.3: The CNN VGG 19 model used in our project

I came across the desired results after running the dataset and constructing the model using the supplied data. With around 90% accuracy, I compared a single illness against another disease's leaves. With about 60% to 79% accuracy, I analyzed one disease with another disease's leaves. The ultimate production chart is shown in Table 7.4 below.

Table 7.4: Disease vs. Disease accuracy

One Disease Vs Another Disease	Specific Disease Vs specific Disease
60% - 79%	80% - 100%

The table shows an output evaluation value of roughly 60% that the phase is at its most severe and 79% that it remains palatable. It's good when it's above 80, and it's considered to be nutritious when it's over 80%. The precision and loss of the graph are displayed in Figure 7.4 below.

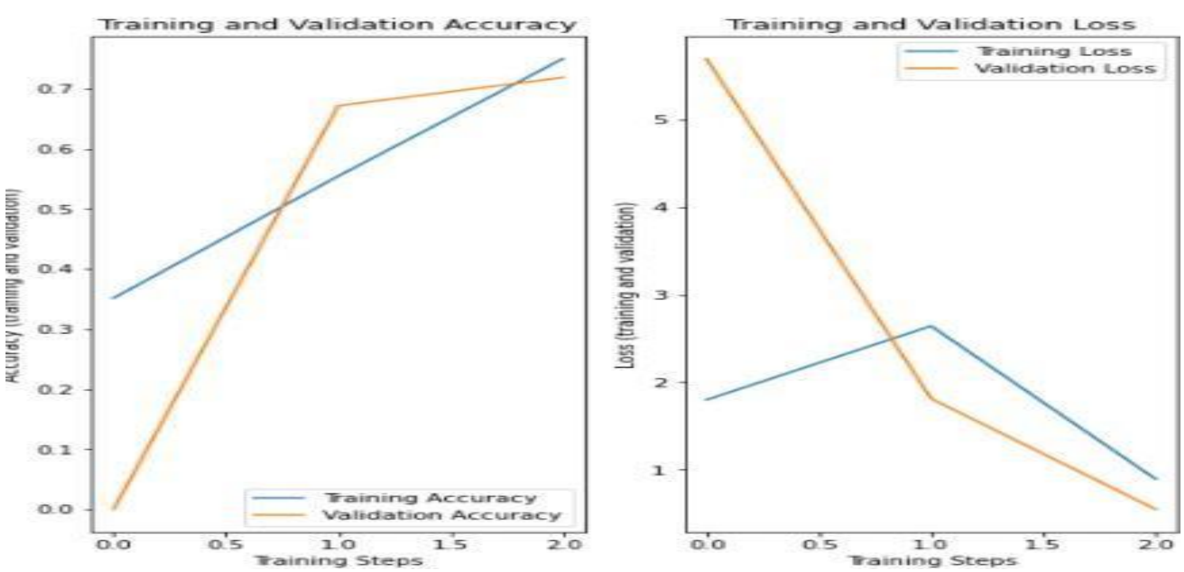

Fig: 7.4: Training accuracy vs. validation accuracy and Training loss vs. validation loss

The exploration has found that this classifier can be used in any type of comparative dataset to compare and predict the accuracy among them, and I can now state that after modifying my model and dataset. 89% of the specific diseases and the specific disease were correctly defined. Additionally, it can distinguish between one disease and another in a range of 60% to 79%. So, from very poor at 60% to mildly rotten at 79%, we will be able to forecast the range of infection and how much there exists.

CONCLUSION

Data has brought us new opportunities and additional complexities in our technological era. Managing fresh data necessitates new approaches and occasionally novel expertise. Judgment wholesome and sick plants one by one is incredibly time-consuming and challenging for government agricultural inspectors. Additionally, it is challenging and time-consuming for farmers and farm owners to identify undesirable plants. So all of those issues may be resolved by this straightforward system. This system may be straightforward but effective. Several adaptive algorithms may evolve in the future to recognize things from visual data. Machine learning using AI-based data and images is crucial for the AI industry. It increases the productivity of our machinery or technologies. Consequently, everyone should have to work with images.

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