ISSN: 2096-3246
Volume 53, Issue 01, Jan, 2021

https://doi.org/10.5281/zenodo.12707114

Natural Date Fruit Environment Classification Using CNN

JANGILI RAVI KISHORE, VIJAYA BHASKAR MADGULA, DIGALA RAGHAVARAJU

Assistant Professor [1,2,3]

jangiliravi.kishore1@gmail.com, vijaya.bhaskar2010@gmail.com,raghava.digala@gmail.com
Department of Computer Science and Engineering, Sri Venkateswara Institute of Technology, N.H 44, Hampapuram, Rapthadu, Anantapuramu, Andhra Pradesh 515722

Keywords:
Convolutional neural network, deep learning, dataset with categories.

ABSTRACT

Several applications in the pre- and post-harvest phases have their needs met by the creation of the date Fruit dataset. Visual yield estimate and mechanised harvesting are the two main uses. Each of the two subsets of the dataset is geared towards one of these two uses. There are a total of 8079 photos of over 350 date bunches taken from 29 different date palms in the first dataset. Each of the five varieties of dates—Naboot Saif, Khalas, Barhi, Meneifi, and Sullaj—is represented in the bunch. Six imaging sessions were used to obtain the photographs of the date bunches using a colour camera. All four phases of date maturity—immature, Khalal, Rutab, and Tamar—were addressed in the imaging sessions. To represent the difficulties in natural settings and date fruit orchards, the dataset is supplied with a high degree of diversity. Images may vary due to factors such as camera angle, scale, lighting, and the presence or absence of bags covering date bunches. Everything in the dataset has been properly labelled according to the harvesting decision, maturity, and kind. This dataset has a wide range of potential uses, such as automated harvesting, fruit identification, segmentation, classification, and maturity study. The second dataset is useful for yield estimates and many others since it includes videos, photos, and weight measurements. In this dataset, we measured the palms' statistics (height, trunk circumference, total yield, number of bunches, and weight of bunches), captured 360° video for each palm, and marked date bunches for chosen palms. Prior to and after harvesting, we photographed each bunch from various angles and transferred the photographs on graph paper. To make referencing, linking, and future expansions easier, both datasets have been coded.

ISSN: 2096-3246
Volume 53, Issue 01, Jan, 2021
https://doi.org/10.5281/zenodo.12707114

Introduction

Because food identification will aid in several tasks, such as name recognition, calorie estimate, ingredient type identification, etc., it has recently become a hot and current study issue. Calorie detection using a convolutional neural network (CNN) technique is the main focus of this research. The four-level methods are usually the foundation of machine learning techniques. Gathering input data is the first stage. At this stage, we gather the supervised and labelled data records that will be used as input. Feature extraction, the second stage, involves identifying characteristics for classification purposes. The analyzers will create the feature selections model based on the class labels and other characteristics that rely on them. We specify the class labels. The next stage is to use a machine learning algorithm to categorise the data. With the help of the classification algorithm, we may use the test data to make predictions about the outcome. Figure 1 provides a clear description of the fundamental method of Machine Learning.

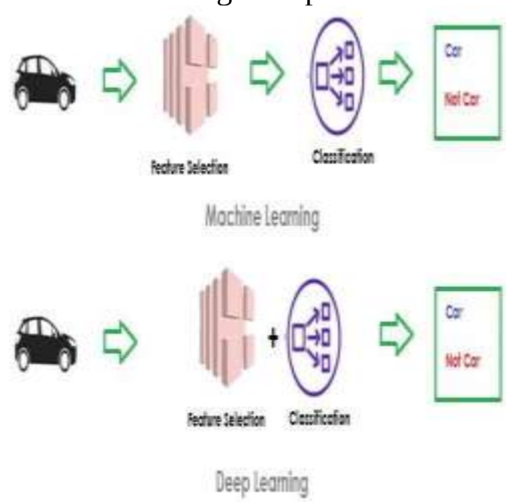


Fig 1. Machine Learning vs. DeepLearning

We presented our Deep Learning-based prediction notion in our article. The idea of deep learning entails three main phases. The gathering of input data is the first, which is similar to machine learning. However, here we may also provide data that is neither organised nor labelled, such as text, photos, etc. Step two allows us to merge the algorithms for feature extraction and classification. Machine learning relies on analysts defining input data characteristics; however, in this case, the features of the input data will be automatically organised and extracted, eliminating the need for analysts to do so. Finally, the outcome will be predicted based on the classifications, much as in machine learning. When it comes to object recognition, CNN models have accomplished a great deal with very little Models for Machine Learning.A wide variety of applications have made use of convolutional neural network (CNN) models to identify objects, such as faces and their expressions. We are using food picture recognition for calories detection by adopting motives from such literatures.

1. RELATED WORK

By collecting and analysing photos of the user's meals, Miyazaki et al. [1] suggested a nutritional management software that can keep track of the user's daily meals. Dietary Application, as suggested in this idea, will use k-means clustering as its classification technique to gather picture characteristics. In this case, they made use of the Bag of Features (BoF) idea, which implies that the food items' colours and forms are the primary factors utilised to gather this data. When making predictions about

ISSN: 2096-3246
Volume 53, Issue 01, Jan, 2021
https://doi.org/10.5281/zenodo.12707114

the food, it then converts this data to pixels and compares them with photos from existing food categories. Here they gathered pictures of five different types of food: grains, meat, fruits, veggies, and dairy.

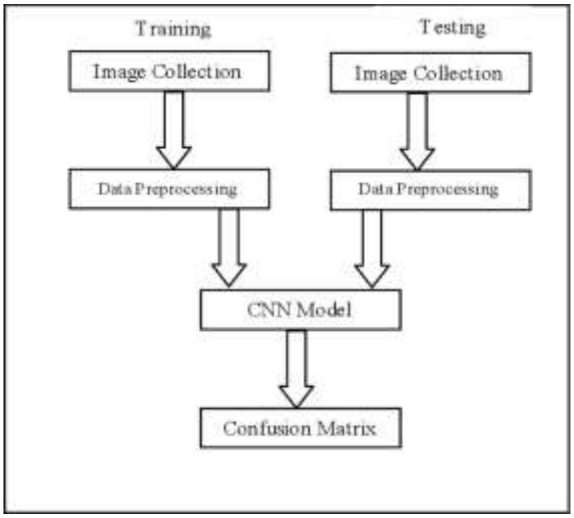


Fig 2: Overview of Dietary Application

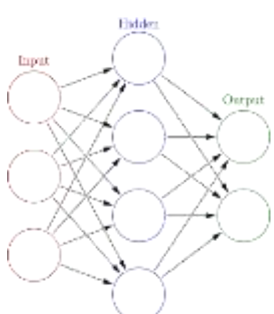
For the purpose of this survey, we will be transforming images of food into pixels, which will then represent future colours and forms (such as circles, areas, etc.). The app will use SV servings to store the photos and their associated data. As mentioned earlier, this idea relies on the features categorization that the developer is required to establish.
Dietary management was suggested by Chen et al. [1] via the use of machine learning classification, which can identify foods for calorie calculation by analysing food photos. In this topic, the authors present the Dietary App, which uses the Support Vector Machine classification technique to gather picture attributes.

PROPOSED FRAMEWORK

Building neural model features for data prediction from unstructured data is the job of Deep Learning, a subfield of AI. Here, we use Convolutional Neural Networks (CNNs) to guess what kind of food is in the picture. We determine the calorie content of a food item by looking at its name in the picture. We can achieve reliable findings based on the collecting of the picture dataset for CNN training.

2. METHODOLOGY

Convolution Neural Networks or covnets area dynamic type of neural networks concepts which are most useful for image processing and natural language processing. It was unique and completely different than neural networks algorithm.



ISSN: 2096-3246
Volume 53, Issue 01, Jan, 2021
https://doi.org/10.5281/zenodo.12707114

In normal neural networks algorithm consist 3 layers, those are input, hidden and output layer. In the input layer it will collect ininput data, and in the hidden layers, a process or calculations done for theprediction, in output layer result will generate. For training and prediction we need set the features of the data in hidden features. But in the CNN Features will automatically calculate according the input data.

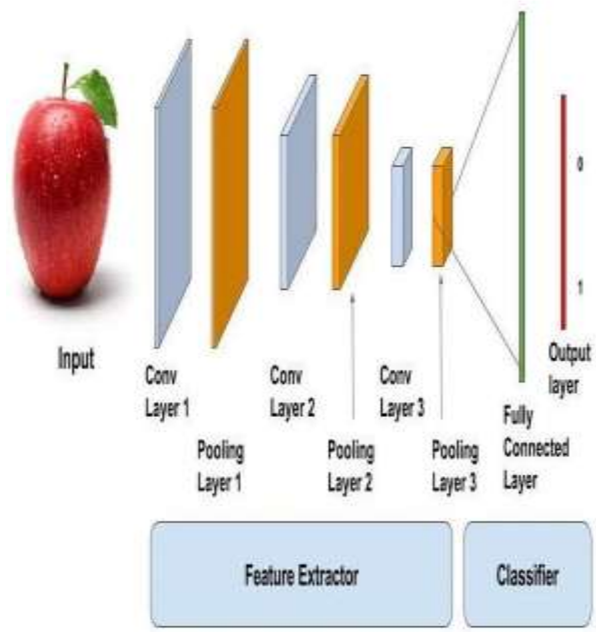


Fig. 3: CNN block diagram

Types of layers in CNN:

- **Input Layer:**

  In this layer it holds the raw data for

- **Convolution Layer**

  In this layer, we can build the core block of the input data, this layer have a set of kernels means learnablefilters using the small blocks of the data, and learn features of the data.

- **Activation Function Layer**

  This layer will apply element wise activation function to the output of convolution layer. Some common activation functions are RELU, Sigmoid, Tanh, Leaky RELU, etc.

- **Pool Layer**

  Pooling layers are used extract thefeatures from the single size of the data splitting to multiple layer. We can get the features of the data and reduce computation cost.

ISSN: 2096-3246
Volume 53, Issue 01, Jan, 2021
https://doi.org/10.5281/zenodo.12707114

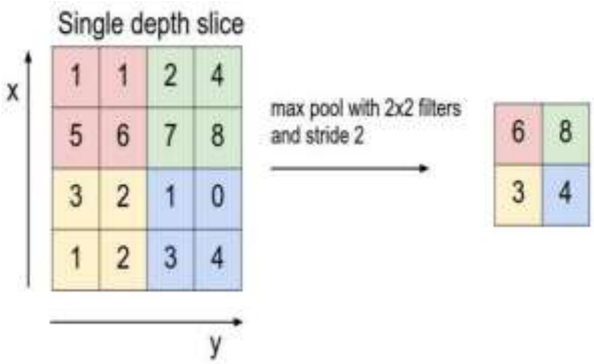


Fig 4: Pooling Layer

In this above example the data [1,1,5,6] convert to one set as 6, and [2,4,7,8] alsoconvert to 8.

For input layer, we have taken 10,000images of 10 categories of the food items.

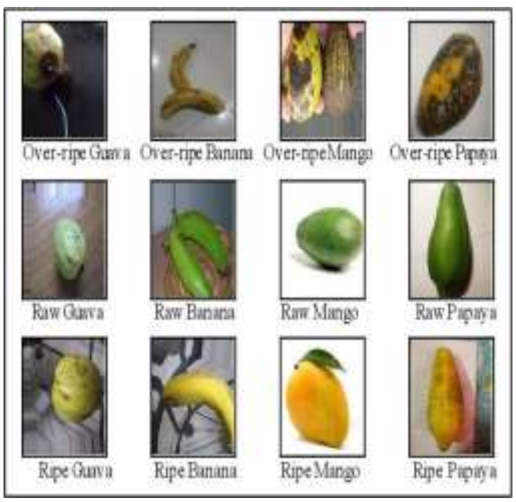
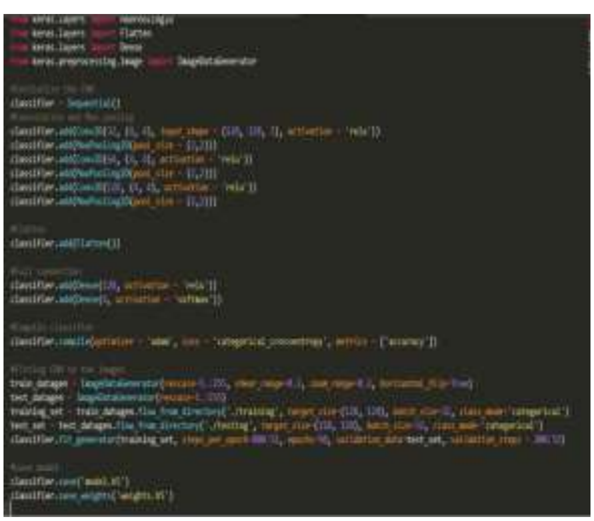


Fig 5: Snapshot of Images of the ‘beignets’ category images of training dataset.

Based on dataset we create training modelusing CNN



ISSN: 2096-3246
Volume 53, Issue 01, Jan, 2021

https://doi.org/10.5281/zenodo.12707114

3. EXPERIMENTAL RESULTS

Class No.	Class Name	Training Image Dataset	Testing Image Dataset
0	OverRipeBanana	811	151
1	OverRipeGuava	1219	328
2	OverRipeMango	573	152
3	OverRipePapaya	433	108
4	RawBanana	1073	237

Fig 6: Dataset under Study

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_2 (Conv2D)            (None, 50, 50, 32)        416
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 16, 16, 32)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 16, 16, 64)        8256
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 5, 5, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 1600)              0
_________________________________________________________________
dense (Dense)                (None, 64)                102464
_________________________________________________________________
dense_1 (Dense)              (None, 64)                4160
_________________________________________________________________
dense_2 (Dense)              (None, 12)                780
=================================================================
Total params: 116,076
Trainable params: 116,076
Non-trainable params: 0
```

Fig 7: Model of CNN

ISSN: 2096-3246
Volume 51, Issue 01, Jan, 2019
https://doi.org/10.5281/zenodo.12707114

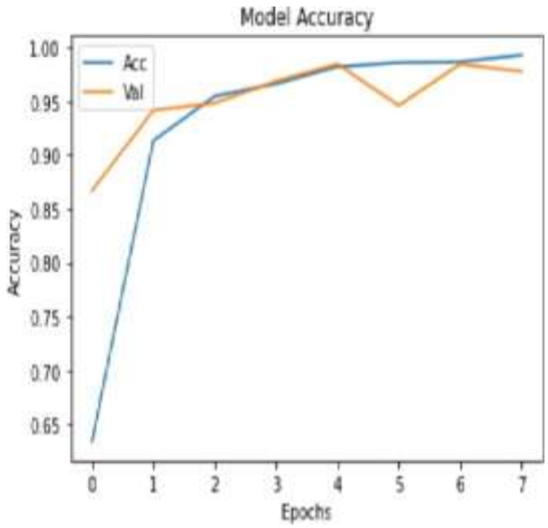


Fig:8 Model Accuracy

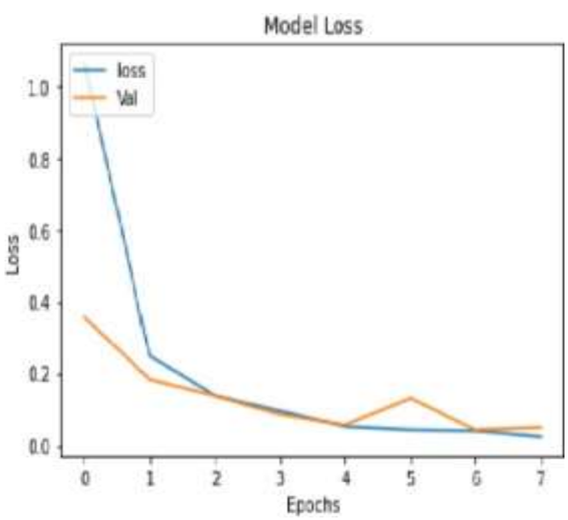


Fig:9 Model Loss Accuracy

CONCLUSION

An excessive amount of data was suggested using deep learning. Date fruit bunches were categorised using three models: kind, ripeness, and harvesting choice. Each classification challenge made use of transfer learning with fine-tuning. We looked at AlexNet and VGG-16, two convolutional neural network (CNN) models that have already been trained. We used a big picture dataset of five date kinds throughout all maturation phases to construct a strong machine vision system. To reflect the difficulties of working in both natural settings and date fruit farms, the dataset was intentionally generated with a high degree of variability. WORK TO COME Moving forward, we want to enhance the dataset by include test photographs taken from several date orchards. We will also look at more modern CNN models that reduce computational complexity and memory use. The date fruit maturity detection conundrum, which includes labelling regulations and interference between phases of ripeness, is another subject that needs more investigation.

ISSN: 2096-3246
Volume 53, Issue 01, Jan, 2021

https://doi.org/10.5281/zenodo.12707114

REFERENCES

[1]Corporate Statistics of the Food and Agriculture Organisation (2016). Postal Service—Stat. Retrieved: October 18, 2018. [On the web]. The URL for this data is: http://www.fao.org/faostat/en/#data/QC. [2] Date Palm Cultivation, first edition, Rome, Italy: FAO, 2002, by Z. Abdelouahhab and E. Arias-Jimenez. [3] "Evaluation of eld test of harvesting system for picking dates fruits based on robotic arm" (Al-Janobi and Abdulwahed 2012) in Proceedings of the International Conference on Robots and Associated High-Technol. Equipment in Agriculture, pages 183–188. Y. Edan, O. Ben-Shahar, R. Mairon, E. Barnea, and K. KapachComputer vision for fruit harvesting robots: current state and future problems, International Journal of Computer Vision Robots, 3, 1, 434, April 2012. [5] "Machine vision algorithm for robots to harvest strawberries in tabletop culture greenhouses," published in "Environment and Agriculture: Food and Agriculture" in 2008, is authored by P. Rajendra, N. Kondo, K. Ninomiya, J. Kamata, M. Kurita, T. Shiigi, S. Hayashi, H. Yoshida, and Y. Kohno. In their 2014 March article titled "Vision-based control of robotic manipulator for citrus harvesting," S. S. Mehta and T. F. Burks discuss the use of computers in agricultural computing. "Development of a real-time machine vision system for the surveillance of 595598 in the Proceedings of the 2004 Annual Conference on Apple Harvesting Robots. Proc. Res. Bull. Agric. Res. Centre, 2003, pp. 518, "Development of a neural network classier for date fruit varieties using some physical attributes" (authored by A. I. Hobani, A. Thottam, and K. Ahmed). [9] "Date fruits classication using probabilistic neural networks," published in the December 2007 issue of the Agric. Eng. International CIGR Journal, by M. Fadel. The article "Date fruits classication using texture descriptors and shape-size features" was published in January 2015 in the Engineering Applications of Artificial Intelligence journal and was written by G. Muhammad.