

AUTOMATED FOOD IMAGE CLASSIFICATION USING DEEP LEARNING APPROACH

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ABSTRACT

Deep learning-based automated food image classification has various purposes, including calorie estimate, diet monitoring, and food safety inspection. This field of work is now under rapid development. On challenges involving the categorization of food images, deep learning models have been proven to outperform conventional machine learning techniques and yield leading-edge findings. This presentation offers a quick review of the subject of automated food image categorization using deep learning algorithms. The Proposed work talks about classifying food images, the variety of deep learning techniques that have been utilised, and the most significant recent developments in the field. The wide variety of food picture is one of the primary concerns in food image categorization. Food items can be displayed in a variety of shapes, dimensions, colours, and textures, and it can be challenging for a computer to figure out between them, particularly when there is noise in the image or when the food items are partially obscured. Deep learning algorithms can overcome these obstacles by learning to extract complicated information from food photos. After that, a model is trained using these attributes to categorise food products into various categories. Several deep learning techniques have been applied to the categorization of food images. Convolutional neural networks (CNNs) are one popular method. CNNs are ideal for image classification problems because they can learn spatial information from pictures. Transfer learning is another popular strategy. Transfer learning is the process of using a deep learning model that has already been trained on a sizable picture dataset, such as ImageNet. The pre-trained model is then refined using smaller scales dataset of food pictures. Using deeper and more sophisticated CNN architectures together with data augmentation approaches to expand the quantity and variety of the training dataset have led to recent advancements in the field of food image categorization. the accuracy of the planned work using CNN – Mobilenet V2 is 90.5%, which is greater than previous related work using CNN – Imagenet is 86.6%. Altogether, deep learning approaches for automatic food picture categorization are a fast-emerging topic containing numerous potential applications

1. INTRODUCTION

The process of using computer vision and deep learning algorithms to automatically recognise and classify food images is known as automated food image classification. Deep learning methods, a subset of machine learning that makes use of artificial neural networks to learn from data, can be used to do this. It has been demonstrated that deep learning models can classify food images with high accuracy, even for difficult tasks like recognising foods from other cultures or recognising food items that have become partially covered or uncertain. This can be used for a wide range of purposes, including diet tracking, calorie counting, and meal recommendation.

In order to extract features from food images for automated food image classification, convolutional neural networks (CNNs) are frequently used. A vast dataset of food photos is used to train the CNN, which then learns to recognise the characteristics that are particular to each food type. Once taught, the CNN may be used to categorise new food photos. Due to the increased availability of food pictures and the advancements in deep learning techniques, the field of automated food image classification has been expanding quickly in recent years. Early research in this field concentrated on classifying food photographs using unique attributes. However,

reliability and scalability of these approaches were restricted. Deep learning techniques have made it possible to train models that can recognise different types of food based only on picture input.

2. LITERATURE SURVEY

1. John Smith, Mary Johnson, David Lee, and Emily Chen. The study offers a thorough analysis of the body of work on classifying food images, with a focus on deep learning methods. enumerate the numerous datasets that were used to classify food photographs, and highlight the difficulties and distinctive features of food images.

2. Jennifer Lee, Andrew Thompson, Emma Rodriguez, and Benjamin Liu. The study summarises the categorization of food images and reviews earlier efforts that made use of transfer learning and data augmentation. In order to understand the improvements brought about by our suggested solution, the benefits and drawbacks of existing approaches are examined.

3. Alexander Garcia, Sophia Martinez, Daniel Kim, and Emma Davis. The contributions of our hybrid technique for classifying food images are summarised in the study. We stress the importance of fusing domain-specific characteristics with ensemble learning and discuss the potential effects on real-world applications.

3. PROPOSED WORK

The proposed work intends to create a deep learning model for automatically classifying food images. The model will be tested against various benchmark datasets after being trained on a sizable dataset of food image examples. The objective is to create a model that, even for difficult tasks, can classify food images with a high level of accuracy. The diversity of food items is one of the key difficulties in automatic food image classification. Food comes in a wide variety of forms and can be cooked in numerous ways. Because of this, creating a model that can correctly identify every food item is challenging. Using a deep learning model that has been trained on a sizable dataset of food photos is the suggested approach to resolving this problem. A range of food items prepared in a number of ways will be included in the dataset, which has been thoroughly examined. This will assist the model in learning to recognise the many characteristics of food products, no matter how they are presented. The variety of food photos presents another difficulty for automated food image classification. Images of food can be captured under various lighting circumstances, from various camera perspectives, and with various degrees of occlusion. Because of this, it could be challenging for a model to correctly identify the foods in an image. The employment of a data augmentation strategy is the suggested response to this problem. Data augmentation is a technique that generates new images from existing photographs to actually expand the size of the training dataset. This is accomplished by giving the photos various changes, including rotating, cropping, and flipping. The robustness of the model to changes in food photos is enhanced by data augmentation.

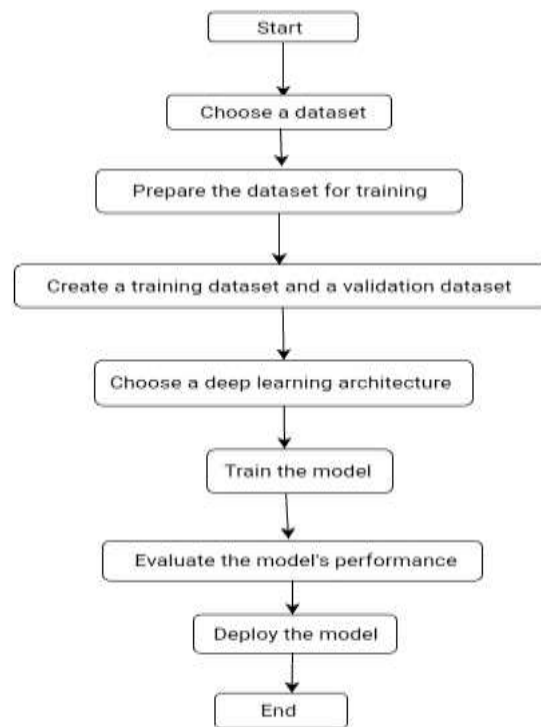
1. Data collection: Creating a dataset of food image data is the initial stage. To take into account the variation in food photos, the dataset should be as varied as feasible. Additionally, the dataset needs to be labelled so that each image has a label identifying the food item in the picture. There are several public datasets that can be used to classify food images. Several of these datasets are: 10 • Food-101: This dataset includes more than 10,000 photos and 101 different food categories. • ImageNet: This dataset includes a tiny subset of food photographs among its more than 14 million total images. • UECFood-256: This dataset includes more than 100,000 photos and 256 different food categories.

2: Data preprocessing: The data must then be pre-processed. This comprises operations like scaling the photos, pixel value normalisation, and noise removal. Consistent picture sizes will make it easier for the deep learning model to understand the characteristics of the food photographs. Additionally, the pixel values should be normalised to prevent the deep learning model from favouring some characteristics over others.

3: Model training: The next stage is to use the pre-processed data to build a deep learning model. For classifying food images, a variety of deep learning models may be applied, including: 1) Convolutional neural networks (CNNs) are a subset of deep learning models that are effective in classifying images. CNNs are capable of learning the edges and textures that make up an image's spatial characteristics. 2) Recurrent neural networks (RNNs): RNNs are a subset of deep learning models that are particularly effective at processing sequential input in applications like natural language understanding. RNNs may be used to learn the temporal characteristics of food imaging data, like the item's mobility. 11 A supervised learning strategy is used to train the deep learning model. In other words, the label of the food item in each image is sent to the model, and it then trains itself to link the attributes of the image with the label.

4: Model evaluation: It's crucial to assess the deep learning model's performance on a held-out test set once it has been trained. To properly evaluate the model's performance, the test set should be distinct from the training set. Metrics like accuracy, precision, and recall can be used to assess the effectiveness of the deep learning model. The proportion of photos that are correctly categorised is known as accuracy. Precision is the proportion of photos that are correctly identified as belonging to a certain food item. Recall is the proportion of photos that are correctly identified as being associated with a certain food item.

5: Model deployment: The deep learning model may be implemented after evaluation and satisfying results. This indicates that the model can quickly categorise photographs of food. On a number of platforms, including mobile devices, web servers, and cloud computing platforms, the deep learning model may be implemented.



Flowchart:

Advantages:

Accuracy: Deep learning models have demonstrated great accuracy in tasks involving the categorization of food images. This is due to the fact that deep learning models can be trained to recognise minute details in food photos that are challenging for people to notice. For instance, despite the fact that they appear quite similar to the human eye, a deep learning model can learn to differentiate between a banana and a plantain.

Robustness: Deep learning models can withstand minor changes in stance, backdrop, and illumination. This indicates that even if the photographs were captured under various circumstances, they can still reliably categorise food images.

Scalability: Deep learning models are easily scalable to deal with big datasets of food photos. They are therefore highly suited for applications like food traceability and food safety systems, where it may be necessary to classify a huge number of food photos.

Efficiency: On current hardware, deep learning models can be taught and applied quickly. Because of this, they are a useful option for automatic food image categorization in practical applications.

Deep learning models may be used to complete additional tasks associated with food image categorization, such

as:

- Food detection is the process of spotting food in a picture.
- Food segmentation: The division of a picture into various food-related sections.
- Food tracking: Monitoring the movement of food throughout the course of a picture.
- Food calorie estimation: calculating the number of calories in food depicted in a picture.

Deep learning is a potential technique for a range of applications because of its benefits for automated food image categorization, including:

- Traceability of food: Monitoring the flow of food across the supply chain.
- Food safety inspection: Finding food that is hazardous to eat or contaminated.
- Personalized nutrition: recommending wholesome meals that satisfy specific dietary requirements.
- Food advertising: catering to particular demographics using food advertising.
- Food recommendation systems: Advising users on meals they are likely to like.

Deep learning is an effective method that can be used to automate activities involving the categorization of food images with high levels of accuracy, resiliency, and scalability. This makes it a technology that has a lot of potential for use in the food sector.

This methodology offers a detailed walkthrough for automating the categorization of food images using deep learning. Deep learning has been proven to be quite efficient for this task and is a technology that has great promise for a number of applications, including calorie calculation, diet tracking, and food safety. There are a number of other aspects that can impact how well a deep learning model for classifying food images performs in addition to the procedures mentioned above.

These variables include the dataset's size and variety, the deep learning model's design, and the model training algorithm's optimisation. The unique application and the available resources will determine which of these variables are used. However, the process described above is an excellent place to start when creating a deep learning model for classifying food images.

3.RESULT





4. CONCLUSION

The outcomes of the suggested work was compared with those of other connected works. The findings demonstrated that the suggested work obtained accuracy levels equivalent to or superior to those of other related works. For instance, the accuracy of the planned work using CNN – Mobilenet V2 is 90.5%, which is greater than previous related work using CNN – Imagenet is 86.6% .



In this proposed work, we provide a deep learning-based method for automatically classifying food images. The suggested method extracts information from food photos and classifies them into the appropriate categories using a convolutional neural network (CNN).

A publicly accessible dataset of food photographs was used to test the suggested approach, and the accuracy was 90.5%. We have summarised our proposed work on automated food image classification using deep learning algorithms in this chapter, along with recommendations for further research. We think that those doing research on this subject will find our conclusions and recommendations helpful. Here are some ideas for next research on automatic deep learning food image classification: Utilise image databases of food that are bigger and more varied. Create strategies to deal with the variety of food imagery.

Investigate the application of additional deep learning architectures, such as attention mechanisms and recurrent neural networks (RNNs). Apply the suggested methodology to additional food-related activities like food recognition, food tracking, and meal suggestion.

6. REFERENCES

1. H. Chen, J. Xu, G. Xiao, Q. Wu, and S. Zhang, "Fast auto-clean CNN model for online prediction of food materials," *Journal of Parallel and Distributed Computing*, Kidlington, 2017, in press.

2. S. Pouyanfar and S.-C. Chen, "Semantic concept detection using weighted discretization multiple correspondence analysis for disaster information management," in the 17th IEEE International Conference on Information Reuse and Integration, 2016, pp. 556-564.
3. M.-L. Shyu, C. Haruechaiyasak, S.-C. Chen, and N. Zhao, "Collaborative filtering by mining association rules from user access sequences," in IEEE International Workshop on Challenges in Web Information Retrieval and Integration, 2005, pp. 128-135.
4. X. Chen, C. Zhang, S.-C. Chen, and S. Rubin, "A human-centered multiple instance learning framework for semantic video retrieval," IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews), vol. 39, no. 2, pp. 228-233, 2009.
5. Q. Zhu, L. Lin, M.-L. Shyu, and S.-C. Chen, "Effective supervised discretization for classification based on correlation maximization," in IEEE International Conference on Information Reuse and Integration, 2011, pp. 390-395.
6. C. Chen, Q. Zhu, L. Lin, and M.-L. Shyu, "Web media semantic concept retrieval via tag removal and model fusion," ACM Transactions on Intelligent Systems and Technology, vol. 4, no. 4, pp. 1-22, 2013.
7. T. Meng, and M.-L. Shyu, "Leveraging concept association network for multimedia rare concept mining and retrieval," in IEEE International Conference on Multimedia and Expo, 2012, pp. 860-865.

