Machine Learning in Packaged Food Product Classification: A Review

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Abstract

Packaged food products are the final product items that consumers regularly purchase and have to be replenished or replaced. Classification of packaged food products has been essential for industries since the origin of these packaged food products to decide the class of a particular product according to its size, shape, price, quality, etc. To improve the efficiency and effectiveness of packaged product processing, industries are investing heavily in the automation of the entire process from production to distribution. For automation purposes, packaged product classification through machine learning plays a significant role to classify the products using various techniques like CNN, KNN, and SVM. This paper present a comprehensive review of machine classification of packaged food products at various stages of their life cycle such as manufacturing, packaging, and distribution. The purpose of the review is to demonstrate the applicability of machine learning based classification to find out which approach and technique are efficiently working and also application areas still uncovered in the relevant field.

Keywords: Packaged food products, Classification, Machine Learning, CNN

1. Introduction

Packaged food products are ready-to-use processed goods that are easily accessible for end-user consumption. Compared to labor intensive methods of processing or eating in raw form, these packaged food products are much more convenient to use and save the user time and effort. [1]. Thus, the demand for these processed products has increased rapidly due to the convenience and urbanization of societies. Another factor contributing to the dependence on these processed products is industrialization which began at the end of the 18th century and has continued since then machines are continuously replacing the manual workforce to make that industrial produce cost-effective and more competitive in the market. As the world has already transitioned to industry paradigm 4.0, where artificial intelligence and machine learning are replacing human involvement in all essential occupations [2]. So, the industries that deal with these ready-to-use packaged food products are heavily investing in artificial intelligence and machine learning to reduce manual errors and automate the entire field i.e. from manufacturing to distribution. To facilitate this, automatic classification is required through One of the prominent machine learning methods applied in these industries is classification using different techniques of machine learning.

The classification process involves two steps: a learning phase that involves building a classification model, and a classification step that deals with predicting class labels for supplied data using the model created in the learning step.[3].

Although, deep learning comes under the area of machine learning the purpose here is to check which techniques are more accurately working in the current scenario of classification. The concluding remarks are discussed in the conclusion section regarding the same. The following sections have detailed machine learning introduction, approaches, and ML techniques.

1.1 Machine Learning

Machine learning is concerned with creating intelligent machines that make rational judgments. The purpose of machine learning is ensure the machines to learn in form of input data, statistical techniques, validation, and feedback by understanding the patterns of data and by creating models that can be understood and utilized by a human. However, it is different from traditional computational methods since those are the collections of computer-programmed instructions that are used to solve problems. Machine learning is used in various areas from healthcare to stock market predictions. Further sections 1.2 and 1.3 are discussed machine learning approaches and machine learning techniques respectively.

1.2 Machine learning approaches

The most commonly used machine learning approaches are explained in the following subsections:

1.2.1 Supervised Learning

In supervised learning, the desired outputs are labeled on the inputs. Comparing the model's actual output to the predicted outputs enables the identification of inaccuracy and updating the model as necessary. Inputted data is analyzed for patterns through supervised learning that also predicts values for new, unlabeled data. Statistically predicting future events from specific previous data is a common use of supervised learning. To forecast upcoming movements, it could use information gathered from the past to predict the share market [4].

1.2.2 Unsupervised Learning

Unsupervised learning takes unlabeled input data and relies on the learning algorithm to identify patterns in the input data. Unsupervised learning aims to unearth hidden patterns in datasets, but may contain a feature learning objective as well that enables the machine to learn automatically from the given representations to categorize raw data. Unsupervised learning is used for fraud detection in credit card purchases by tracking unusual behavior transactions. Other use cases such as images of an object can be used as input data for the algorithm to find similarity and group the other images of objects having the maximum similarity [5].

1.3 Machine learning techniques

Machine learning relies on statistics, which includes pattern classification, regression, and probability, Regression (Logistic and polynomial Regression), KNN, Bayesian classification, and Decision Trees are related techniques discussed in the following subsections.

1.3.1 Regression

Regression comes under the category of a supervised learning model that is used to examine the relationship between two variables where one independent variable is manipulated to find the relationship with one dependent variable. The regression enables obtaining prediction of future values or events as it can be used to discover the dependent variable where the independent variable is already available. The categories of algorithms used are Linear regression, Polynomial regression, and Logistic regression [6].

1.3.2 K-Nearest Neighbours (KNN).

KNN belong to the supervised learning category that classifies the data members by measuring the distance between the K value and available data members. Labeled data are required to train the K-nearest neighbours model. KNN can classify unlabeled data using the information provided by analyzing the k number of the nearest data points. If most of the data members of the unknown data set belong to a certain category of the trained data set, then that unknown dataset also belongs to that category. The value of K in this method is usually an integer value and the output of the algorithm may vary on the selection of the K value [6].

1.3.3 K-means clustering

K-means clustering is the most frequently used algorithms in unsupervised learning approaches. The clustering algorithm is a technique for automatically categorizing a collection of unlabeled data into various groups. The data from the same category must all have similar properties for this approach to work. However, it can only be used with continuous data, and before clustering, the number of categories must be manually specified [7].

1.3.4 Decision Tree

In decision tree classifier, each leaf node represent the classification result, each branch represents the output of a judgement result, and each internal node represents a judgement on an attribute. The use of decision trees to visually depict decisions and promote an educated decision-making process. Using input variables, decision tree learning attempts to develop a predictive model for unlabeled data. In the predictive model, the branches reflect the qualities of the data that are determined by observation, and the leaves represent inferences regarding the target value of the data. Decision tree learning separates the source data into subsets based on attribute value tests, which are then repeatedly iterated on each subset. The recursion operation will conclude when a node's subset equals its target value. [8].

1.3.5 Random Forest

There is no correlation between the several decision trees that make up Random Forest. A new input sample is entered to execute the classification task in the random forest, and each tree in the random forest chooses its own decision. The ultimate result will be the choice that appears the most frequently across all categorization outcomes. [9].

1.3.6 Artificial neural networks (ANN)

The structure of an ANN (artificial neural network) is rather simple as compare to other CNN or RNN. It comprises a simple perceptive that calculates the weighted total of its input data and output data using mathematical operations. Neurons are the name of the nodes in the graph. There are three levels exist in a simple neural network. First one is the input layer or the initial layer, followed by the hidden layer that may contain more than one layer and the last one is the output layer. The input layer takes input data and passes it to the hidden layer for processing. Results of probability prediction are obtained by using the output layer. Supervised models called artificial neural networks are frequently applied to regression and classification problems. [10].

1.3.7 Back-Propagation

Back propagation networks are error-trained multilayer feed-forward networks. Back-propagation neural networks are popular. This calculates the network weight loss function gradient. To reduce loss function, the optimization technique feeds the gradient back to weights. It necessitates an output that is already known for each input data to estimate the loss function gradient. The back-propagation algorithm repeats incentive propagation and weight change using forward and backpropagation. The input data is passed to the hidden layer and then transmitted to the output layer. To optimise weight, the partial derivative of the goal function to each neuron's weight is calculated layer by layer to create a ladder. Weight loss concludes education. Error equals expected value prevents network learning [11].

1.3.8 Convolutional Neural Networks

CNN an important technique that contain convolution, nonlinear, pooling, fully connected, and output layers. Convolutional neural networks output the picture category probability. The input image can be read as various matrices, and the output is the most likely thing it represents. The convolutional layer calculates the input image's dot product with the filter's weight matrix. Layer output is result. The filter will repeat the dot product technique over the image. Depending on the job and model structure, the hidden layer may have many convolutional and pooling layers [12]

2. Review of literature

In this section, the different application areas of consumer packaged food products covered under machine learning classification techniques by various authors are discussed, and then a separate summary for both ML and DL in tabular form is discussed.

Sinha, Banerjee and Chattopadhyay (2022) suggested a solution based on deep learning to solve the issue of recognizing items on retail store racks from an image of the rack. The method uses a two-stage pipeline for object detection and recognition that consists of an image encoder based on ResNet-18. The encoder classifies the objects into a particular class and an object localizer based on Faster-RCNN that finds the object regions in the rack picture. The tests run on the Grozi-32k and GP-180 data sets to confirm the viability of the suggested model. On the GP-180 dataset, the mean average precision (mAP) was 82.70%, while the product recall was 89.70% [13].

Menichetti *et al.* (2022) proposed a method based on machine learning that can precisely forecast the level of processing for any food. The findings showed that the food supply in US market have over 73% of that is ultra processed. It demonstrated that the increased reliance on these ultra-processed foods is the major cause for the risk of developing disease metabolic syndrome, diabetes, angina, high blood pressure, and biological age and lowers vitamin bioavailability. Ultimately, it was discovered that substituting foods with less processed versions can greatly lessen the harmful effects of highly processed food, indicating that the availability of information about the level of processing, which is now not proper available to consumers, could enhance population health [14].

Amani and Sarkodie (2022) developed the application of machine learning in the management of meat supply based on industrial paradigm 4.0 and sustainable development goals. A classification model was built for the suggested application using the deep CNN and PSO methods. The two types of red meat samples in this dataset—whole and spoiled—were taken from a Turkish supermarket. The model's accuracy was attained at 100% [15].

Hafez *et al.* (2021) developed a method to automatically classify the ever-evolving product list into 3-level food taxonomy. The study concentrated on three distinct approaches: a score-based ranking system, conventional machine learning methods, and deep neural networks. The main goal is to give an automatic classification tool that only provides one result: the best Variety for a New Product first choice. Other two possibilities, however, that took into account the advantages for the corporation were also taken at second, that contains the two most suitable variants for a new product, and third includes the three most suitable variants for a new product. By reducing the difficulty of categorizing a new product into two or three categories instead of 159, both of them would also aid in the categorization process. The findings show that FKNN is most accurate in the first, followed by K nearest neighbour. However, in the second and Third, the score-based algorithm outperforms FKNN, that comes in second [16].

Davies *et al.* (2021) developed a KNN based algorithm for packaged food products such as food and beverages to predict the added-sugar content. The results of the algorithm has similar accuracy as in the method developed by Louie *et al.* [17] for added sugar prediction. The accuracy of the proposed approach was 89% [18].

Zhu *et al.* (2021) reviewed the machine learning based techniques that can be used in the food processing sector, including standard and deep learning approaches. To accurately detect the quality and type of food, the image processing is a crucial part of machine vision. Because food is the foundation of human health, stability and social progress so it is a significant concern for the entire the social order. Food processing at every phases from cultivation to harvest, storage, preparation and consumption, must be taken into account to ensure food safety and quality. Image processing advances in machine vision can help businesses increase the effectiveness of food preparation [19]

Davies *et al.* (2021) designed a KNN-based technique to forecast the fibre content of packaged foods and beverages based on publically available information. The algorithm is more precise in predicting fibre content than the existing manual approach. The KNN based algorithm provides comparatively higher performance as compared to earlier neural network nutrition prediction methods. These forecasts can be used to track the amount of fibre in the packaged food available in the Australian market and to guide activities aimed at boosting fibre consumption. The KNN algorithm's classification accuracy was estimated to be 71%. The system was particularly effective at detecting goods with a lot of fibre (Precision: 0.76 recall 0.81). [20]

Saha & Manickavasagan (2021) proposed a method for using several machine learning techniques to evaluate hyper spectral images to ensure the food quality. It discusses the fundamentals of hyper spectral imaging as well as the benefits and drawbacks of each ML technique. The ML based algorithms demonstrated speedy and highly accurate processing of hyper spectral pictures of food products, enabling accurate classification. Since choosing the most efficient wavelengths from the hyper spectral data considerably reduces the computing burden and processing time, it opens up more possibilities for real-time applications. [21]

Tsakanikas *et al.*(2020) developed a universal, global workflow for analyzing spectroscopic data to identify raw food types using FT-IR. The proposed method performed flawlessly on sample data with high variation in batch, storage time, temperature, spoilage, and packing. The obtained spectra reflect this variation and show the method's robustness and accuracy. Moreover, it can confidently assert that FT-IR, which is widely regarded as a "gold standard" technique for many applications and research regarding food safety that provides rich sample data and allow the effective assessment of various food sample properties. The method's performance is consistent under all food storage conditions that also make it suitable for widespread use in the detection of the type of raw food. As evidenced by the results, it can conclude that the proposed workflow and the resulting classifier were able to distinguish seven food types with a 100% accuracy, with the data in the training and testing phases showing significant variation in terms of batch origin and storage conditions. As a result, the classifier can be reliable and unaffected by random fluctuations within a single food category [22].

Wong *et al.* (2019) developed the data set from the scratch for the use of deep learning algorithms in industrial applications, specifically for detecting packaged goods in a warehouse. To detect and recognize distinctive grocery products in a warehouse environment, this technique tries to develop a computer vision system. The approach created a synthetic dataset using 3D models created by using photogrammetric methods on actual things. A convolutional neural network called Inception V3 is trained using 100K artificial images across 10 classes. In case of testing set product images of real supermarket, accuracy was attained at 96% [23].

Fuchs, Grundmann & Fleisch (2019) created a CNN-based object detection and classification model for the retail environment. An open-source collection of 300 vending machine images with 15k annotated instances of 90 goods is utilized as the data set. According to the findings, only six images are sufficient to get an accuracy of 90% in image classification, while roughly 30 images are required to achieve an accuracy of 95% [24].

Hossain, Al-Hammadi & Muhammad (2019) developed a framework for fruit classification based on deep learning. In the suggested framework, a light model based on CNN having six layers and a VGG 16 based on deep learning was evaluated. The framework was tested using two different datasets of distinct sizes and complexity. On dataset 1 and dataset 2, the VGG-16 had an accuracy of 99.75% and 96.75 %, respectively. With 99.49% accuracy on dataset 1 and 85.43% accuracy on dataset 2, the CNN model demonstrated great accuracy as well. Both of the models outperformed the two existing approaches on dataset 1 once their performances were compared to two other already existing methods [25].

Geng *et al.* (2018) proposed an innovative method that integrates feature based harmonizing, one-shot learning, and a coarse to fine technique to successfully find and identify instances of product images in a retail store in real environment. To get accurate results, the suggested approach follows three steps: finding candidate product using recurring characteristics, creating an attention maping to amplify the characteristics, and identifying product instances by combining recurring characteristics and attention maping with one-shot learning. The proposed approach performs better in the performance comparison than the other state of the arts. The performance mAP of VGG16 is better on GP-20 with 0.9235 mAP, and VGG16+ATmapSIFT is better on the other three datasets with mAP of 0.7393, 0.6555, and 0.8579 on Grozi-3.2K, Grozi-120, and Gp-180, respectively [26].

Ribeiro *et al.* (2018) developed a deep learning architecture for adaptive learning for optical character verification. The method was tested on a dataset of food packaging labels and proposed to automate the identification of products with to-use-by dates. A CNN was used in the proposed approach and modified for it. To achieve better separation and adaptation, centroids computed for both CNNs were combined and used in a k-nearest neighbour adaptation technique after CNN-extracted representations had first been clustered using a k-means. The final phase of testing yielded a performance accuracy of 76.4% on first dataset and marginally increased the accuracy of second dataset to 97.1% [27].

Tonioni, Serra & Di Stefano (2018) presented a quick and efficient solution for the problem of identifying food items on store shelves. The proposed technique divides the task into three steps such that a class neutral object, Recognition by KNN based on a global image descriptor and Final enhancement to further improve the performance. Modern deep learning techniques are used in all three steps: the items are recognized by a cutting-edge CNN (Detector), an additional CNN is trained to learn the image descriptor (Embedder), and local cues important for refining are extracted as MAC attributes computed together with the global embedding. The tests demonstrate that, although being incredibly quick, the pipeline compare favorably to the state of the art on publicly available datasets for performance evaluation [28].

Cavallo *et al.* (2017) proposed a technique employing the CNN methodology to estimate the fresh-cut iceberg lettuce quality level through packaging. The CNN methodology is very much appropriate for image recognition and processing tasks. For training purpose, the stochastic mini-batch gradient descent technique was used to optimize the parameters of the CNN. For the purpose of validation, a validation dataset was used to assess the CNN. In particular, a classification accuracy of 0.979 was attained after 100 training epochs. [29].

From the aforementioned literature review, it is abundantly obvious that machine learning are utilized in a variety of packaged food products industry application domains, including production, packaging, selling, and distribution. Below is a summary of the aforementioned literature regarding application domains and their respective machine learning techniques.

Table 1: Application areas covered under machine learning for packaged food products

Author’s	Application Areas	Classification Methods/techniques	Conclusion/Results
Cavallo *et al.* (2017)	Quality evaluation	CNN	There is a minor loss because of the coverage of bags, the achieved accuracy was 83.33% instead of 86%
Ribeiro *et al.* (2018)	Optical Character Verification	CNN, KNN, k-means clustering	The final performance accuracy was achieved at 76.4% on dataset 1 and 97.1% obtained on dataset 2

Tonioni ,Serra & Di Stefano (2018)	Product recognition	CNN, KNN	The Pipeline compares favorably to the previously work done on public dataset
Geng *et al.* (2018)	Product Recognition	CNN	The VGG16 performs better with 0.9235 mAP and VGG16+ATmapSIFT performs better on the other three datasets with mAP 0.7393, 0.6555, and 0.8579 on all three datasets
Hossain, Al-Hammadi & Muhammad (2019)	Fruit Classification	CNN	The light architecture and VGG-16 model achieved 99.49% and 99.75% accuracy respectively
Wong *et al.* (2019)	Product classification	CNN	Achieved an accuracy of 96% on real supermarket product images
Fuchs, Grundmann & Fleisch (2019)	Product Classification	CNN	The overall accuracy of around 95% achieved
Tsakanikas *et al.* (2020)	Raw food categorization	Regression SVM classification	The developed classification model results in an accuracy of 95%
Banús *et al.* (2021)	Quality control	CNN	DenseNet161 achieves an accuracy of 0.99, precision 0.99, recall 0.99, F-score 0.99

Davies *et al.* (2021)	Predict the Dietary Fiber of Packaged Foods	KNN	The accuracy was calculated to be 71%
Hafez *et al.* (2021)	Classification of Retail Products	KNN, fuzzy KNN, eXtreme Gradient Boosting, and Multilayer Perceptrons	In top 1, PSO was 84.59%, in Top 2 rate was 90.46% and Top 3, MLP was 91.09 %
Davies *et al.* (2021)	Added Sugar prediction of Packaged Foods	KNN	The classification accuracy of the approach was 89%
Menichetti *et al.* (2022)	Prediction of Food Processing	Random Forest	The result shown more than 73% of the total U.S. food supply is ultra processed.
Amani and Sarkodie (2022)	Classification of wholesome meat from spoiled ones.	CNN, PSO	The accuracy achieved at 100%
Sinha, Banerjee and Chattopadhyay (2022)	Product Recognition	Deep Neural Network	The mAP achieved 82.70% and recall achieved 89.70%

From the above summary table, it can be seen that the classification has been performed at various stages of the product's life cycle.

According on Table 1, The CNN has a very large number of applications in product recognition and computer vision. CNN is far more accurate than all other machine learning techniques combined. After CNN, machine learning approaches KNN and SVM have been used more frequently than other techniques, and both have relatively higher accuracy.

In a broader context, classification approaches based on machine learning have been applied by different authors to the four application domains of Manufacturing & Packaging, Quality control, Marketing & Distribution, and a domain intended specifically for the health perspective of consumers, i.e. consumer centric approaches.

Table 2: Classification according to the application areas

Author's Name	Application Areas			
	Manufacturing & Packaging	Quality Control	Marketing & Distribution	Consumer-centric
Menichetti *et al.* (2022)				✓
Amani and Sarkodie (2022)	✓			
Sinha, Banerjee and Chattopadhyay (2022)			✓	
Banús *et al.* (2021)	✓			
Davies *et al.* (2021)				✓
Hafez *et al.* (2021)			✓	
Davies *et al.* (2021)				✓
Tsakanikas *et al.* (2020)			✓	
Hossain, Al-Hammadi & Muhammad(2019)		✓		
Wong *et al.* (2019)			✓	
Fuchs, Grundmann & Fleisch (2019)			✓	
Ribeiro *et al.* (2018)		✓		
Tonioni, Serra & Di Stefano (2018)			✓	
Geng *et al.* (2018)			✓	
Cavallo *et al.* (2017)		✓		
Total	2	3	7	3

The classification techniques used for the first three categories—manufacturing & packaging, quality control, and marketing & distribution—are industry-centric, whereas the fourth category consumer centric includes the classification of packaged food products from the consumer's point of view, so that the consumer is aware of the products that are in daily use. The percentage distribution below (figure 1) reveals that machine learning approaches used extensively in industries cover 80% of the market due to their substantial investments, whereas the other portion only covers 20%. It demonstrates that the areas from the consumer's perspective must be investigated concerning the packaged food products.

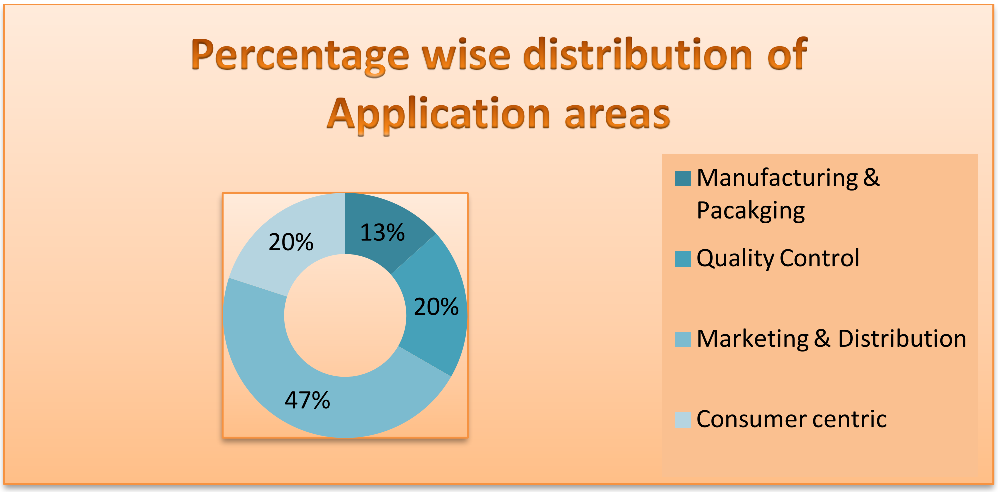

Fig 1: Percentage-wise distribution of application areas

3. Research gap

From the above analysis, it has been found that most of the ongoing researches of machine learning classification techniques were limited to improve the profitability of enterprises, and the machine learning framework as a whole is focused on industrial applications. The review of literature provides the idea of the repeated use of specific machine learning techniques that too in the industrial applications only. The more exploration is required related to application of machine learning in relation to consumer's perspective to raise their awareness of the things they use in daily life. Therefore, the objective of AI coexistence with humans can be achieved. Also, the classification of packaged food products based on ingredients needs to be done through machine learning as it can help the consumer in choosing the healthy product more efficiently rather than going through all the ingredients manually.

4. Conclusion

The literature review assists readers in comprehending the classification application areas of machine learning that have been researched for packaged food products in recent years. According to the survey, CNN is used in a wider range of domains, from manufacturing to distribution, followed by KNN, SVM, and other algorithms. In the classification of product images, the accuracy of CNN is higher than that of all machine learning algorithms. On the other hand, the k-nearest neighbour algorithm is more precise than other machine learning methods. Hence, based on the above literature survey, the machine learning have come to matured stage of automation in the packaged food products industries considering some remaining challenges of accuracy and efficiency. The application of machine learning framework is largely dependent on industrial applications to make food processing more efficient with accuracy close to 100%. The future work should involve the applications in support of consumers' perspective by focusing primarily on consumer health and preference using machine vision.

Authors' contribution

The author Rajesh kumar had performed literature search for the article. The author Dr. Dilbag singh had performed data analysis and critically revised the work.

Acknowledgement

The author Rajesh Kumar is very much thankful for the financial support from University Grants Commission (India) under their junior fellowship scheme and also the University for providing the research facilities.

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