Using advanced Deep Learning Models and Computer Vision Algorithms to Automate Tea Classification and Analysis

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Abstract: This research uses advanced deep learning (DL) and computer vision methods to expedite the analysis and classification of brewed tea in an effort to advance beverage analysis. We have created an automated method that combines spectral imaging to measure the nutritional, vitamin, and mineral content with convolutional neural networks (CNNs) to extract features from high-resolution photos of different teas. For improved data processing and model efficiency, the study also makes use of transfer learning (TL) with pre-trained models, recurrent neural networks (RNNs) and generative adversarial networks (GANs). Segmentation strategies and object detection algorithms help to improve the categorization process. The use of ensemble methods is intended to increase robustness and accuracy. The results highlight the effectiveness of CNNs in accurately classifying liquid teas, especially when combined with transfer learning. The research also emphasizes how useful item identification and segmentation are in separating out beverages in intricate visual fields, as well as how GANs can be used to enhance data. The study's output is a deep learning framework that can be scaled and interpreted, and it offers the tea sector a number of advantages, similar consumer insights, product differentiation, and quality control.

Keywords: Machine Learning (ML), Computer Vision, Deep Learning, Data Preprocessing, Beverage Analysis, Brewed Tea, Classification, Identification, Health Benefits, Nutrient Profiling, Color Detection

Introduction: Overview of Advanced DL Models

The capacity to evaluate and comprehend data, particularly historical data & visual data, becomes more and more important as technology develops. DL has become quite effective at sifting through massive volumes of data and identifying relevant information [17]. DL models are essential for the identification and classification of beverages, especially tea [18]. They make it easier for characteristics to be automatically extracted from photos, which helps the system recognize intricate patterns and generate precise predictions.

Over time, sophisticated DL models have undergone significant evolution. The word "deep" refers to these models' capacity to process data over numerous layers. Every layer picks up a representation of the data, and the representations get more abstract and sophisticated as the data moves through the network.

The sophisticated DL models and computer vision algorithms [14] that are especially pertinent to the task of beverage identification and classification will be covered in this work. We investigated each model's architecture, benefits, as well as uses and cover the following models:

CNNs, are essential for tasks involving feature extraction and image classification [1,15]. CNNs are well-known for their effectiveness in image processing. Due to their specialized design, they excel at processing grid-like data, pixels in an image, making them ideal for pattern recognition [23-26]. There are normally three distinct layers in a CNN physical layout/architecture: Convolutional Layers, the feature maps are downsampled by introducing pooling layers after convolutional layers, and fully connected layers carry out the neural network's higher-level reasoning after numerous convolutional and pooling layers.

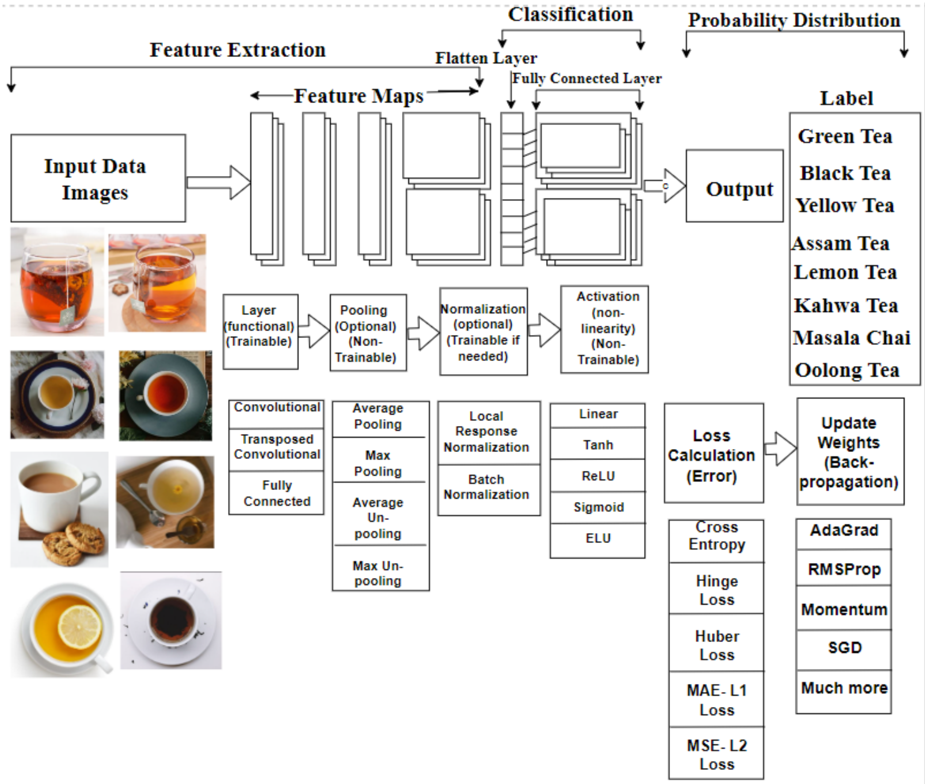

Figure 1. Architecture of CNN

CNNs can be used to classify beverages such as tea using a model trained on photos of the various sorts of tea in liquid form. The convolutional layers are to be eventually able to identify unique patterns, including the tea's hue/colour and texture. After pooling layers have reduced the dimensions, fully connected layers will use the extracted features to classify the type of tea. Variations in color, texture, and even shape add a new dimension of complexity to the task of categorizing brewed tea. Adapting CNN architectures to meet these needs is often crucial [13]. General features, such as edges or textures, are typically well picked up by the lower convolutional layers. However, capturing color nuances can be more crucial for tea classification. The model's ability to catch color changes can be improved by experimenting with different filter sizes and numbers in the initial convolutional layers. Liquid tea, once prepared, might appear differently depending on the illumination. The model can be made more adaptable to a wide variety of imaging situations by the use of data augmentation techniques such as brightening, changing the contrast, or slightly altering the hue [11]. Activation maps of the convolutional layers can be shown to reveal which areas and characteristics of the tea are receiving the most attention. This can shed light on whether or not the network is successfully learning significant features.

Model size can be reduced without sacrificing accuracy and need special attention to techniques includes quantization and trimming. By using model quantization, the 32-bit precision of the weights must be reduced, say, to 8 bits, for this purpose. Because of this, the model size may be drastically reduced, which is essential for mobile deployment. Neurons that do not significantly contribute to the output can be removed through pruning.

RNNs are useful for learning sequences and can be used with CNNs to do more complex tasks [2]. RNNs are superior to other methods for processing natural language and analysing time series. However, they are not as good at directly classifying images as CNNs. A RNN may handle sequences by repeatedly traversing their elements and updating their state with relevant data.

GANs networks can be used for data augmentation and are well-known for producing fresh data that is comparable to the training set. Both the generator and discriminator networks of a GAN are trained at the same time. The discriminator is trained to assess the quality of the data generated by the generator. New photos of different types of tea can be generated using GANs, making them useful for data augmentation [3]. When data is limited, this can be especially useful. It entails familiarising small adjustments to the dataset or creating new data points via DL. The primary function of GANs in this work is to produce synthetic data sets that mimic the training data [22]. They could be used to create similar tea pictures, but they're not great for sorting data.

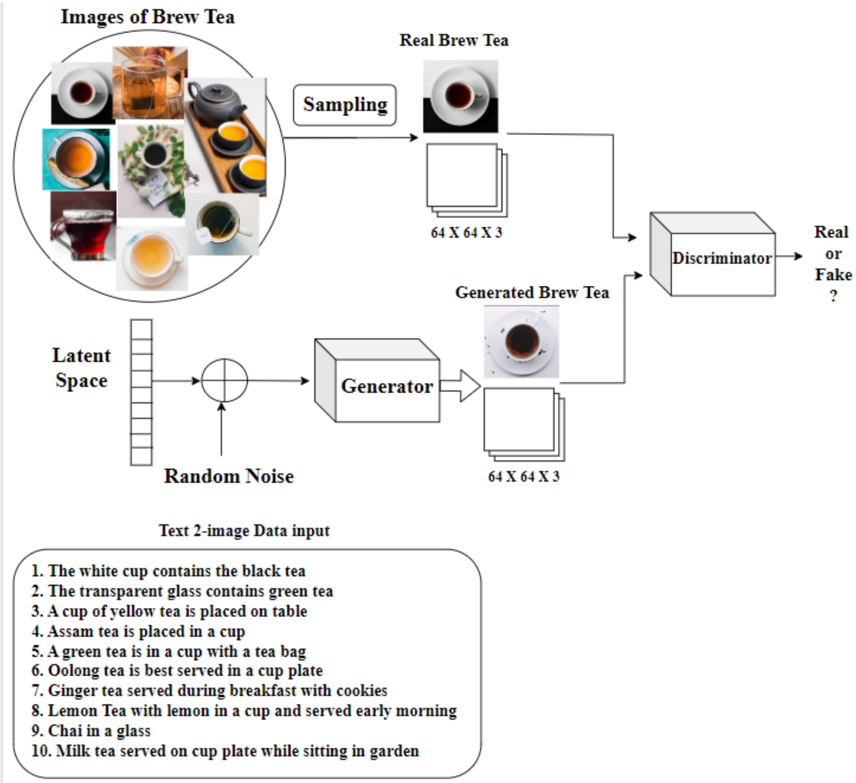

Figure 2. Architecture of GANs

TL and Pre-trained Models are used when the dataset is small, using pre-trained models can greatly shorten the training period and boost performance. Here in this work, a model that has already been trained, it can take advantage of its pre-learned characteristics to improve the accuracy with which we classify teas without having to collect a huge dataset [4]. Pre-trained models, can be fine-tuned to achieve better results in tea classification with minimal additional training time required.

Object Detection Algorithms: When the task entails both identifying and locating objects in images, models such as SSD (Single Shot Multibox Detector) and YOLO (You Only Look Once) are indispensable [5]. This can be helpful if the system needs to recognize several different drinks in the same picture. Object detection is the process of locating and recognizing various items inside an image. Object detection can be used to find the teacup in a picture, but a classification technique is needed to label the tea itself.

Segmentation Algorithms: These are helpful for breaking a picture up into different parts, which facilitates analysis and classification [6]. Separating the tea from its surroundings or isolating the liquid in the cup can facilitate analysis.

Ensemble Methods: Increasing accuracy and robustness by combining several models. When performing a classification task, it is typically possible to improve accuracy and reliability by mixing models that have been trained on distinct subsets of the dataset or that have alternative architectures [7].

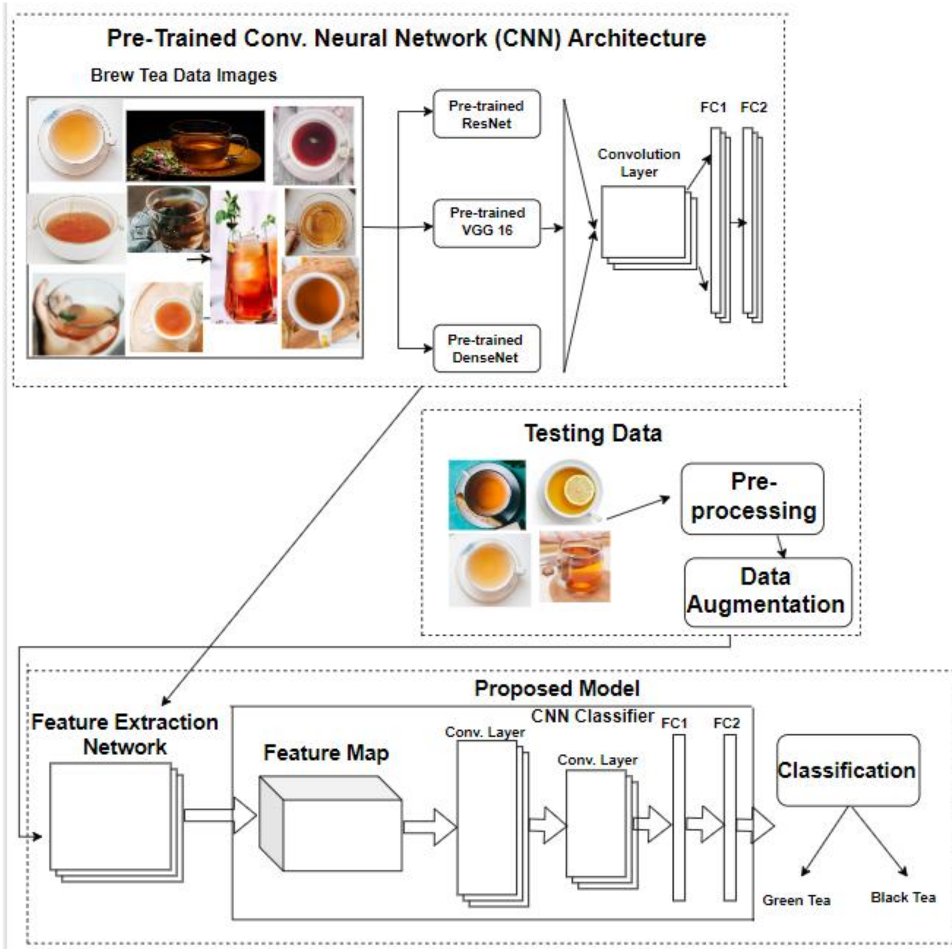

Figure 3. Physical Layout of Transfer Learning and Pre-trained Models

The table below outlines the strengths and weaknesses of the available deep learning models for recognizing and categorizing tea in its brewed and served form:

Table 1. Deep learning methods for tea recognition and categorization: strengths & shortcomings

Algorithm/Model	**Identification Purpose**	**Classification Purpose Preference**	**Time for Training**	**Model Complexity**
CNNs	No	Yes	Moderate	Moderate
RNNs	No	No	Long	High
GANs	No	No	Very Long	Very High
Transfer Learning & Pre-trained Algorithms (VGG16 or ResNet)	No	Yes	Short	Moderate
Object Detection models (YOLO & SSD)	Yes	No	Moderate	High
Segmentation Algorithms	Yes	No	Moderate	High
Ensemble Algorithms	No	Yes	Long	High

CNNs are likely the best appropriate model for detecting and classifying prepared tea in its liquid state. Pre-trained models and TL are two ways to cut down on training time and improve results. Preprocessing or applications that require finding the tea or isolating it from the background may benefit from object detection and segmentation techniques. The classification of tea is not a task well suited to RNNs or GANs. By learning about these cutting-edge DL models and computer vision techniques, we can select the best ones to implement in our beverage identification and classification system [20].

Table 2 representing the machine learning algorithm (supervised and unsupervised models) [19], deep learning algorithm, and advanced deep learning algorithm [14-18, 20, 27] with the names of different models, which are preferred for identification and classification of prepared tea when the data is in the form of prepared tea in liquid form and in a cup.

Table 2. Preferred algorithms for identification and classification of brewed tea

Category Type	**Model/Algorithm Name**	**Identification Preference**	**Classification Preference**
ML (Supervised type)	Support Vector Machine (SVM)	No	Yes
	Decision Trees (DT)	No	Yes
	Random Forest (RF)	No	Yes
	Logistic Regression	No	Yes
	K-Nearest Neighbors (KNN)	No	Yes
ML (Unsupervised Type)	Hierarchical Clustering	No	No
	K-Means Clustering	No	No
	Principal Component Analysis (PCA)	No	No
DL	CNNs	No	Yes
	RNNs	No	No
Advanced Deep Learning	GANs	No	No
	TL (ResNet, VGG16)	No	Yes
	Segmentation Algorithms (U-Net)	Yes	No
	Object Detection Algorithms (SSD, YOLO)	Yes	No
	Ensemble Methods (CNN models combination)	No	Yes

Table 3 representing the various types of supervised and unsupervised models, DL models, and advanced deep learning models which are preferred for classifying different types of teas as suggested according to their health benefits, when the data is in the form of prepared tea in the liquid form and in a cup.

Table 3. Preferred algorithms for classifying different brewed teas and suggestion according to their health benefits

Category Type	**Model/Algorithm Name**	**Classification Preference**	**Health Benefits Preference**
ML (Supervised)	Logistic Regression	Yes	No
	SVM	Yes	No
	RF	Yes	Yes
	DT	Yes	Yes
	KNN	Yes	No
ML (Unsupervised)	Hierarchical Clustering	Yes	No
	K-Means Clustering	Yes	No
	Principal Component Analysis (PCA)	No	No
DL	CNNs	Yes	Yes
	RNNs	No	No
Advanced Deep Learning	GANs	No	No
	TL (using ResNet, VGG16)	Yes	Yes
	Object Detection Algorithms (e.g., SSD, YOLO)	No	No
	Segmentation Algorithms (U-Net)	No	No
	Ensemble Methods (CNN models combination)	Yes	Yes

First, supervised learning algorithms can be useful for categorizing tea varieties and making recommendations about their health benefits. They are adept with both quantitative and qualitative information. Second, photos can be classified into different varieties of tea and possibly have health benefits suggested based on the visuals using DL, notably CNNs and TL with pre-trained models. Third, while unsupervised learning [35] can be used to group various teas into categories, it may not be useful for making recommendations about the health advantages of tea without labeled data. Fourth, because reinforcement learning (RL) is not normally employed for classification tasks, it cannot be applied here.

Table 4 shows the Nutrient values, vitamins, and minerals in various teas can be efficiently identified using DT, RF, SVM, KNN, AdaBoost, and XGBoost. Labeled data is required for training these models. VGG-16, Inception V3, and MobileNet, among others, are excellent at extracting features from photos via deep learning. These models can be quite helpful in determining the vitamin and mineral content of various teas based on their appearance when combined with TL. Unsupervised learning methods, which are typically used for clustering or reducing dimensionality, are ineffective in determining nutritional levels, vitamins, or minerals since they do not employ labeled data for training. Nutrient values, vitamins, and minerals in teas are not frequently identified using GANs, object detection techniques, and segmentation algorithms.

Table 4. Preferred algorithms for identification of nutrient and vitamins values of different types of brewed teas

Category	**Model/Algorithm Name**	**Nutrient Values Identification Preference**	**Vitamins Values Identification Preference**	**Minerals Values Identification Preference**
ML (Supervised)	DT	Yes	Yes	Yes
	RF	Yes	Yes	Yes
	SVM)	Yes	Yes	Yes
	Logistic Regression	Yes	Yes	Yes
	KNN	Yes	Yes	Yes
	AdaBoost	Yes	Yes	Yes
	XGBoost	Yes	Yes	Yes
ML (Unsupervised)	K-Means Clustering	No	No	No
	Hierarchical Clustering	No	No	No
	PCA	No	No	No
DL	CNNs	Yes	Yes	Yes
	VGG-16 CNN Model	Yes	Yes	Yes
	Inception V3 CNN Model	Yes	Yes	Yes
	MobileNet CNN Model	Yes	Yes	Yes
Advanced DL	TL (VGG16, ResNet)	Yes	Yes	Yes
	GANs	No	No	No
	YOLO, SSD	No	No	No
	Segmentation Algorithms (U-Net)	No	No	No
	CNN models combination	Yes	Yes	Yes

Different types of teas include varying amounts of nutrients, vitamins, and minerals; therefore, picking the optimal algorithm or model for this task requires thought into a number of factors, including accuracy, training time, interpretability, scalability, and the nature of the data. Comparison is shown in table 5.

Table 5. Optimal algorithm or model based into a number of factors for different brewed teas

Algorithm/ Model	**Accuracy**	**Training Time**	**Interpretability**	**Scalability**	**Suitability for Nutrient Identification**
DT	Moderate	Fast	High	Moderate	Good for simple relationships
RF	High	Moderate	Low	High	Robust but less interpretable
SVM	High	Slow	Moderate	Moderate	Good for high-dimensional data
Logistic Regression	Moderate	Fast	High	High	Good for simple linear relationships
KNN	Moderate	Slow	High	Low	Good for small datasets
AdaBoost	High	Moderate	Low	Moderate	Good for complex relationships
XGBoost	High	Moderate	Low	High	Good for complex relationships
CNNs	High	Slow	Low	High	Good for image data

VGG-16 CNN Model	High	Very Slow	Low	High	Exceptional for image data
Inception V3 CNN Model	High	Very Slow	Low	High	Exceptional for image data
MobileNet CNN Model	High	Moderate	Low	High	Exceptional for mobile devices
TL	High	Moderate	Low	High	Exceptional for leveraging pre-trained models
Ensemble Methods	High	Slow	Low	High	Robust but less interpretable
LightGBM (Advanced)	High	Fast	Moderate	High	Exceptional for large datasets
CatBoost (Advanced)	High	Moderate	Moderate	High	Handles categorical features well

Table 5 data shows that DL models, including different CNNs, have great accuracy but long training times. They shine, however, when dealing with image data, which could prove crucial if tea's nutrient identification relies on visual inspections. Due to their high accuracy, good scalability, and faster training times compared to DL models, gradient boosting methods like XGBoost or more advanced ones like LightGBM and CatBoost may be the better choice in situations where you have structured data (here, tabular data with nutrient information).

The size of the dataset, the availability of training hardware, and the need for interpretability all play a role in determining the appropriate model to use. In this case, Transfer Learning with a pre-trained model like VGG-16 or MobileNet could be the best option due to their high accuracy and ability to exploit prior knowledge [8]. The data would consist of photos of liquid tea. However, XGBoost, LightGBM, or CatBoost might be better suited to the task at hand because of their superior performance on tabular data.

1.1 Appropriate Dataset Size with Hardware Requirement and Model Interpretability

When tabular data is used for gradient boosting techniques, the dataset size, hardware requirements, and model interpretability may depend on the issue complexity and accuracy. For gradient-boosting techniques, the dataset size may be a few thousand to several thousand records. As the dataset grows, the model learns the patterns better. Big data doesn't bother LightGBM or CatBoost.

A modern, multicore CPU (quad-core or above) is needed. Dataset size affects RAM needs. 8GB to 16GB of RAM should be enough for small-to-large datasets (a few thousand to several hundred thousand records). Multiple million-record datasets may demand 32GB or more storage. GPUs can speed up training on huge datasets, but they are not required. XGBoost and LightGBM are GPU-accelerated.

Gradient boosting models are harder to understand than linear regression or decision trees for predicting the nutrient, vitamin, and mineral value of tea or drinks because they make a group of DT. Adjusting the model's hyperparameters ensures effective training without overfitting on large datasets. Cross-validation may help evaluate the model's efficacy. TL with pre-trained models has different problems with image data because of the size of the dataset, the technical needs, and the model's ability to be understood. Due to pre-trained models' prior information, TL may work with fewer datasets. When fine-tuning and aiming for high accuracy in a domain, a larger dataset pays off. A few hundred to several thousand images per theme is a decent start. Transfer learning can optimize a smaller dataset, but more photos improve generalization.

Due to their many layers and parameters, DL models like VGG-16 and MobileNet are challenging to interpret. Grad-CAM provides interpretability by displaying the picture regions activated for categorization. Scaling photos to fit the pre-trained model's expected input size is crucial to preprocessing. Freezing the weights of the pre-trained model's early layers can save training time while preserving accuracy because early layers collect general features and later layers are more specialized. MobileNet is also faster and uses less memory than VGG-16 due to its computational efficiency.

When the data contains pictures of tea in a cup or in tabular form, below is a table 6 comparing several algorithms and models for categorizing the tea:

Table 6. Optimal algorithm or model selection based on data type for different brewed teas

Model/ Algorithm	Data Type	Accuracy	Training Time	Interpretability	Scalability	Hardware Requirements	Remarks
KNN	Tabular	Medium	Slow	High	Low	High	Not suitable for image data
SVM	Tabular	Medium	Slow	Low	Low	High	Not suitable for image data
RF	Tabular	Medium	Moderate	Medium	High	Medium	Not fit for image data
DT	Tabular	Low	Fast	High	Medium	Low	Not fit for image data
XGBoost	Tabular	High	Fast	Low	High	Medium	Not appropriate for image data
AdaBoost	Tabular	High	Moderate	Medium	Medium	Medium	Not suitable for image data
CatBoost (Advanced)	Tabular	High	Fast	Medium	High	Medium	Not suitable for image data
LightGBM (Advanced)	Tabular	High	Fast	Low	High	Medium	Not appropriate for image data
CNNs	Image	High	Slow	Low	Medium	High	Appropriate for image data
Inception V3 CNN	Image	Very High	Slow	Low	Medium	Very High	Complex model, good for large datasets
VGG-16 CNN	Image	High	Very Slow	Low	Low	Very High	Deep model, requires large dataset
MobileNet CNN	Image	High	Fast	Low	High	Medium	Efficient, good for mobile devices
Ensemble Methods	Mixed	Very High	Slow	Low	Low	Very High	Combines multiple models
TL	Image	High	Moderate	Low	High	High	Reuse pre-trained models

Tea preparation picture categorization is best accomplished using CNNs [30-33] and TL with pre-trained models such as MobileNet or Inception V3. These models were developed with picture data in mind and are capable of acquiring sophisticated visual characteristics. If it is requiring a middle ground between precision and efficiency, especially on low-powered devices, MobileNet is the best choice. If maximum precision is a top concern and adequate computing resources are available, Inception V3 can be used. By merging the results of numerous models, Ensemble Methods can improve accuracy, but at the expense of greater complexity and resource requirements.

1.2 Selection of DL Models for Tea Classification

Choosing the appropriate DL model is crucial for achieving optimal performance in the challenging task of tea image categorization. This section explores the factors to take into account and the reasoning behind choosing a suitable DL model for categorizing various types of brewed tea. The nature of the data should be the primary factor in choosing a DL model. CNNs are ideally suited to this problem since we are dealing with photos of liquid tea. The spatial hierarchies of patterns in photographs can be captured by CNNs because they were developed with image processing in mind. It also matters how much information can be used for training purposes. In general, a considerable amount of data is needed to successfully train DL models, particularly CNNs. If anyone don't have access to a sizable dataset, it can still use Transfer Learning using pre-trained models. It entails taking a model that has already been trained on a big dataset and refining it with data from a specialized domain. It takes a lot of processing power to train a Deep Learning model, especially a VGG-16 or Inception V3 [34]. A more lightweight architecture like MobileNet, optimized for computational and memory efficiency, can be desirable if computing resources are scarce. Sometimes there is a trade-off to choose between precision and speed. In general, the accuracy improves with the depth and complexity of models like Inception V3, but at the expense of greater computational complexity. Lighter models, such as MobileNet, are more efficient, but they cannot be as accurate. In some contexts, it's not enough for a model to produce reliable results; it's also necessary to know how and why it arrived at its conclusions. Deep learning models are notoriously difficult to interpret, but using Grad-CAM, we can learn more about the features the model is prioritizing. Because of the type of data, the amount of it, the processing power available, and the trade-off between accuracy and speed, MobileNet or Inception V3 seems like a good choice for identifying liquid tea from pictures. If saving time and money are equally important, then the preferable choice is MobileNet. It works wonderfully for use in mobile applications. If maximum precision is a top objective and sufficient computing power is available, Inception V3 is a viable option to pursue. It works wonderfully for tasks that call for extreme accuracy. To sum up, the type and amount of data, the computing power available, and the need for accuracy and speed should all be taken into account when choosing DL models for categorizing tea [37]. Tea categorization can be made easier with the help of unique architectures rather than generic models like MobileNet or Inception V3. To test if tinkering with factors like filter size, number of convolutional layers, and activation function yields better results. Another possible direction to investigate is the use of hybrid models that incorporate features of multiple neural network designs. When a succession of photos is given, for instance, a model that combines CNN-RNN may be able to better capture temporal changes in tea qualities [12, 28-29, 36]. The model could be improved by incorporating attention mechanisms into the network, allowing it to zero in on the most important aspects of the images [16, 30]. Especially if the color and texture of the tea are modest but discernible markers of its classification, this could be very helpful. Image categorization is one area where DL models can greatly benefit from data augmentation. To train the model on more data, random changes like rotation, scaling, and horizontal flipping can be applied to the training images [31]. This aids the model's generalization to novel, unseen images and helps minimize overfitting. In order to train DL models effectively, it is essential to optimize hyperparameters similar batch size, learning rate, and the quantity of training epochs. Methods like grid search and random search can be used to methodically investigate a large number of possible hyperparameter settings until the best one is found [32]. The success of the model assessment relies heavily on using appropriate evaluation measures. Accuracy, precision, recall, F1 score, and confusion matrix are all useful metrics for assessing a model's effectiveness in multi-class classification tasks like tea categorization. In addition, cross-validation during training can help shed light on the model's potential efficacy on new data. After the best possible deep learning model has been trained, it is time to think about how to put it to use in the real world. The processing resources of the deployment platform, the required reaction time, and the simplicity of model updates as new data becomes available. The model needs to be flexible so that it can be updated as new information and tea varieties become available. To maintain the model's efficacy over time, it is recommended to implement a system for continuous learning in which the model is retrained or fine-tuned at regular intervals using new data. Visualizing the activation maps of the convolutional layers is one way to make CNN models more interpretable. This allows one to see what parts of the image trigger particular filters and, hence, what elements the network is likely to be focusing on. This can shed light on which properties of the tea beverage are being employed by the model for classification, which is of particular interest. Grad-CAM and other feature attribution techniques can also be used to learn about the model's decision-making process. This technique uses a heatmap superimposed on the original image to highlight the regions that had the greatest bearing on the model's final verdict.

Conclusions:

This study shows how powerful it is to combine computer vision algorithms with sophisticated DL models for tea's nutrient profile and categorization. When combined with TL, CNNs proved to be the most effective models for image-based tea analysis [10]. The dataset was improved through the use of GANs for data augmentation, and segmentation and object detection algorithms were vital in the process of identifying and evaluating tea within the photographs. Ensemble approaches improved the classification's reliability and accuracy. The study clarifies the significance of model efficiency and interpretability for practical use. The architecture that has been provided has the ability to be implemented in mobile applications, which presents a viable means of augmenting the consumer experience and bolstering the analytical capacities of the tea sector. Additional studies could investigate the integration of more sensory data for an even more thorough analysis and expand the applicability of these models to other beverage types.

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