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Advancements in Coffee Bean Species Classification: A Comprehensive Literature Review on Machine Learning and Image Processing Approaches

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Abstract:

14 studies were reviewed to understand how machine learning techniques can be used to classify different types of coffee beans. The researchers used deep learning models to achieve precise categorization and identified Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) as the leading models with superior accuracy. The report highlights the versatility and effectiveness of various models, emphasizing their dominance in this field. This study also discusses the challenges encountered in comprehending the findings of these models accurately and offers recommendations for future research. The knowledges serve as a foundation for enhancing existing methods and fostering innovative ideas in the development of universally applicable and comprehensive coffee bean classification models.

Keywords **—CNN, ANN, Machine Learning, Coffee Bean, Classification.**

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I. INTRODUCTION

The study of coffee bean species classification is a crucial area of research, with significant implications for both the coffee business and knowledgeable consumers [1]. The categorization of coffee bean species is a crucial aspect of coffee research, highlighting its profound importance in the literature. Accurate identification of coffee bean species is crucial for ensuring quality in the coffee industry. Precise classification of each species is crucial in order to preserve their distinct flavour profiles and aromatic attributes. This classification process guarantees the maintenance of quality standards, which in turn directly impacts consumer satisfaction and loyalty. This categorization acts as a basis for effective supply chain management, enabling comprehensive monitoring and identification of the source and attributes of coffee beans. It is crucial for guiding agricultural operations and aiding farmers in creating customised plans for optimal development conditions. The classification of coffee bean species is essential for studying genetic variations, disease resilience, and unique characteristics related to different species in the field of research and development. This comprehension facilitates the creation of novel coffee varieties, enhances cultivation methods, and bolsters resistance against environmental challenges. The act of identifying and preserving indigenous coffee varieties contributes to the protection of biodiversity. Accurate categorization of coffee bean species is essential for establishing market trends, meeting consumer preferences, and promoting the sustainable and diverse future of the global coffee industry. An essential aspect of this research is its practical utility, notably in the fields of agriculture and the coffee supply chain. [2] Highlights the significance of incorporating computer vision techniques to examine coffee beans, underscoring the crucial role these technologies play in maintaining and ensuring the quality of the beans. This viewpoint clearly aligns with the difficulties encountered by farmers and other parties involved in the supply chain, emphasising the importance of accurate species categorization.

II. BACKGROUND

A. *Machine Learning*

Significant progress in machine learning has been particularly noticeable in the field [3]. Feature assessment entails a thorough analysis of variables or attributes that are crucial in the process of learning. Researchers in the field aim to uncover and optimise these aspects based on to refine the efficacy and efficiency of machine learning algorithms. This thorough examination aids in refining algorithms, guaranteeing their ability to capture pertinent patterns and complexities. The topic of study spans a range of approaches, from supervised to unsupervised learning, with a primary focus on creating strong and widely applicable models [4]. The major objective of this technical advancement is to equip computers with the capacity to acquire knowledge and make predictions by drawing on past experiences [5]. Classification is a fundamental aspect of machine learning, facilitates the classification of data into discrete categories or groups based on fundamental patterns. The research highlights the importance of precise classification algorithms in interpreting complex biological data offering researchers significant insights into relationships and differences among various datasets. Classification processes have great potential in several activities, including genetic profiling [6]. The objective of computer vision is to perceive and understand the visual information present in digital images. Computer Vision research is all about creating digital systems that can process and understand visual input like photos and videos in a way that's similar to how humans perceive the world around them. This field of study is focused on developing technology that can recognize patterns, identify objects, and even understand emotions conveyed through visual media. By mimicking the way humans see and interpret the world, computer vision research is helping to create smarter, more intuitive machines that can better understand and interact with the world around us. The fundamental concept underlying computer vision is to instruct computers in the analysis and comprehension of images at a microscopic level encompassing individual pixels. Machines aim to collect, analyse, and assess visual data via precise software algorithms. Image processing is a distinct process that involves taking an photo as input, carrying out determined operations, and producing an output. Every individual pixel inside the photo undergoes a predetermined sequence of operations during the process of image processing. The image processor performs these actions in a systematic manner, processing each pixel individually. Subsequent operations only begin until the full series is completed. The result of these techniques is obtained by analysing any individual pixel inside the image.

B. *Emerging Machine Learning Methods*

The study of coffee bean species classification in literature is a complex undertaking, motivated by various important factors. [9] research highlights the significant role of advanced methods in ensuring excellence and authenticity of coffee beans. They utilizes infrared spectroscopy and machines for support vector for geographical classification, hence expanding the range of approaches employed. These investigations highlight the urgent requirement for precise and efficient techniques in categorizing coffee bean species, not only for academic research but also for practical purposes in ensuring quality control and managing the supply chain. Given the worldwide nature of coffee commerce, it is crucial to priorities the verification and excellence of the beans in order to uphold consumer contentment and industry benchmarks. The application of machine learning and computer vision algorithms has demonstrated substantial efficacy in assisting the industry in categorizing different kinds of coffee beans, with artificial neural networks (ANN) emerging as the favoured approach for achieving enhanced precision [1]. The combination of image processing techniques and data mining algorithms has resulted in successful results in categorising nutritional inadequacies in coffee plants. It is worth mentioning that the support vector machine (SVM) is particularly remarkable [10]. Decision Trees and ensemble classifiers are one type of machine learning method that have shown impressive performance in accurately identifying different coffee bean species based on detailed shape data. This achievement has been highlighted by [11] and has shown outstanding accuracy rates. Infrared spectroscopy is a highly effective method for classifying coffee bean samples according to their environmental origins, providing a remarkably accurate degree of classification [12]. A detailed investigation about classifying of coffee bean species based on images, utilising the capabilities of machine learning, has highlighted the unexplored possibilities of transfer learning. The newly developed methodology has the chance to greatly enhance the precision of coffee bean quality identification leading to a new age of accuracy and efficiency in the coffee business [13].

Several research have extensively investigated the use of various classifier and remote sensing data for crop classification. [14] and [15] Highlight the efficacy of integrating optical data and radar to enhance the precision of classification. [16] employs a unique methodology by employing spectral indices collected from Sentinel-2A images, resulting in a remarkable overall accuracy of 93.1%. [18] performs a comprehensive comparison analysis that includes standard machine learning, object-oriented categorization, and deep learning algorithms. The results indicate that combining random forest with deep neural network techniques in a synergistic manner achieves the best level of accuracy, reaching 98%. These studies collectively demonstrate the intriguing potential of using different data sources and classification methods to achieve precise and accurate crop classification. The introduction of agroforestry systems in coffee production represents a significant change demonstrating beneficial effects on microclimate, crop productivity, and product quality. Specific species of shade trees, such as Bishofiajavanica and Jacaranda mimosifolia, are identified as highly advantageous contributors to this comprehensive transition [19].

Utilization of Machine Learning in Agriculture and Coffee Industry The rapid use of machine learning techniques has led to significant advancements in coffee bean classification. It have been utilised several strategies to improve the accuracy and efficiency of this process. [20] was the first to use Convolutional Neural Networks to identify green coffee beans. Hung proposed a technique that utilises fatty acids profiling to categorise coffee beans, with a focus on addressing the problem of information loss caused by mixed dimensions in species and roasting degrees [21] enhanced the field by employing a machine learning methodology to classify coffee bean quality, yielding an impressive accuracy rate of 83%. In addition, [22] effectively distinguished between organic and regular coffee beans using 1H NMR profiling, highlighting unique metabolites for each category.

III. NOTABLE STUDIES

Significant progress has been achieved in the subject of coffee bean categorization in recent years, as researchers have experimented with various approaches and advanced models to improve accuracy. With the objective of this literature review to present a thorough examination of the research undertaken on the categorization of coffee beans, highlighting valuable perspectives, approaches, and significant discoveries, the following table summarizes the core findings of these investigations, providing a comprehensive summary of each research undertaking. Some notable studies that lead the advancement are shown with figure of their chosen machine learning method. Every entry comprises relevant details, including the attained level of accuracy, the particular model type utilized, and the characteristics of the dataset employed

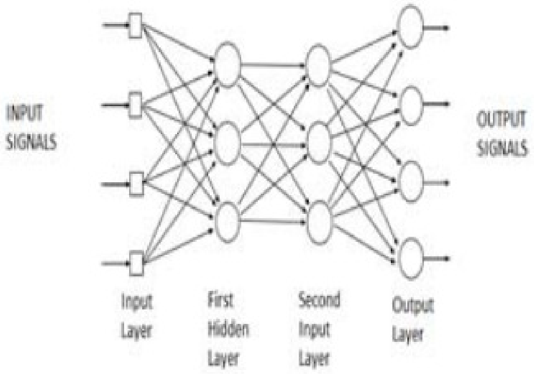
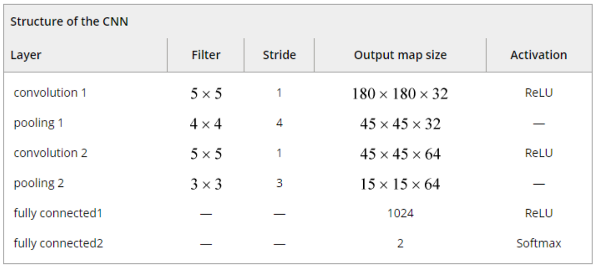


Figure 1. [1] Structure of ANN Model



Structure of the CNN

Layer	Filter	Stride	Output map size	Activation
convolution 1	5 × 5	1	180 × 180 × 32	ReLU
pooling 1	4 × 4	4	45 × 45 × 32	—
convolution 2	5 × 5	1	45 × 45 × 64	ReLU
pooling 2	3 × 3	3	15 × 15 × 64	—
fully connected1	—	—	1024	ReLU
fully connected2	—	—	2	Softmax

Figure 2. [27] CNN Model Architechture

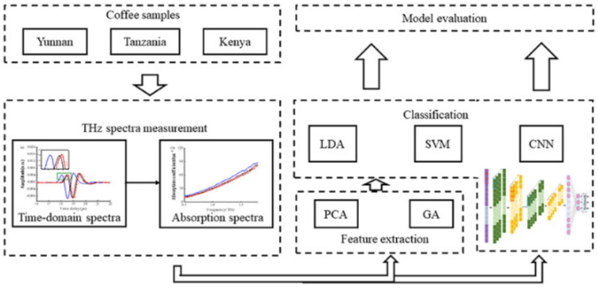


Figure 3. [34] Combined Machine Learning Methods

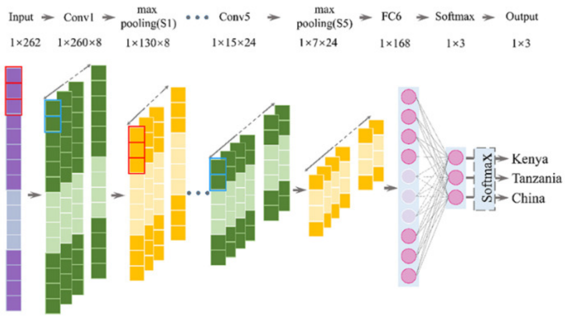
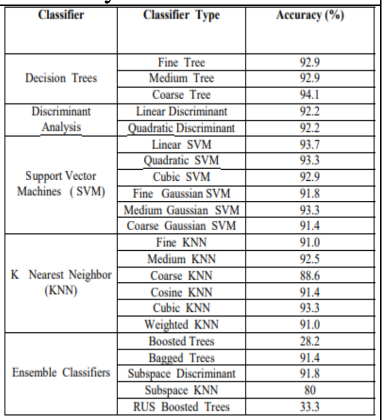
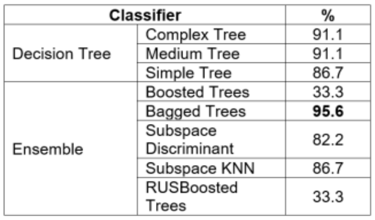


Figure 4. [34] Structure of CNN Model

Paper	Experimental Setup	Datasets used	Method Used	Accuracy
[23]	The images were processed using a laptop computer that has an Intel Core i7-6700HQ 3.5 GHz processor, 4 GB of RAM, and a 1 TB hard disk for storage. The laptop runs on a 64-bit Microsoft Windows 10 Professional operating system. The study utilized MATLAB 2017b, a software that is commonly used for image processing and classification of coffee beans.	255 coffee bean samples were collected from the province of Cavite, with 85 samples per species 1. The photographs were captured using a Sony DSC-W800 camera with a sensor that has the ability of detecting 20.1 effective megapixels	Data Mining (Decision Trees Discriminant Analysis Support Vector Machine K-Nearest Neighbor Ensembles)	
[24]	Started by using Near-Infrared Spectroscopy (NIRS) to measure the absorbance of light at a specific wavelength from 85 individual samples of civet coffee and 85 individual samples of non-civet coffee. They then used a technique	The training dataset for the Feedforward Backpropagation Neural Network (FFBPNN) has a combined total of 65 samples of civet coffee, denoted as samples SA1.1 to	NIRS and ANN	95% to 100% accuracy

Classifier	**Classifier Type**	**Accuracy (%)**
Decision Trees	Fine Tree	92.9
	Medium Tree	92.9
	Coarse Tree	94.1
Discriminant Analysis	Linear Discriminant	92.2
	Quadratic Discriminant	92.2
Support Vector Machines (SVM)	Linear SVM	93.7
	Quadratic SVM	93.3
	Cubic SVM	92.9
	Fine Gaussian SVM	91.8
	Medium Gaussian SVM	93.3
	Coarse Gaussian SVM	91.4
K Nearest Neighbor (KNN)	Fine KNN	91.0
	Medium KNN	92.5
	Coarse KNN	88.6
	Cosine KNN	91.4
	Cubic KNN	93.3
	Weighted KNN	91.0
Ensemble Classifiers	Boosted Trees	28.2
	Bagged Trees	91.4
	Subspace Discriminant	91.8
	Subspace KNN	80
	RUS Boosted Trees	33.3

	called FFBPANN to categorize the absorbance values. The network underwent training to accurately categorize whether a given absorbance measurement refers to civet or non-civet coffee.	SA1.65, and an additional 65 examples of non-civet coffee, denoted as samples SB1.66 to SB1.131. After performing multiple training rounds, the network achieved a sufficient level of accuracy.		
[1]	The images were taken with a Sony DCS-800 20.1 Megapixels digital camera and saved for future editing on a Laptop. The laptop runs on the professional operating system of Microsoft Windows 10 (64-bit) and uses the MatLab R2012a platform.	The coffee beans used in this investigation were sourced from the collection of the National Coffee Research Development and Extension Center (NCRDEC), located at Cavite State University in Indang, Cavite. The sample beans were indicative of various coffee-producing municipalities in Cavite, namely Amadeo, General Emilio Aguinaldo, Mendez, Silang, and Indang.	ANN and KNN	ANN: 96.67% KNN:82.56%
[25]	The researchers took pictures of the coffee bean samples by placing them on a white background and holding a smartphone camera 6 inches above them. The	The coffee beans used in this study were collected from the Cavite State University in Indang, Cavite (National Coffee	ANN	96.67% accuracy

<table>
<tr><td></td><td>camera was set to 1x zoom</td><td>Research Development and Extension Center (NCRDEC)). 180 images were used in the process. Size is 4160 x 3120 pixel then cropped into 256 x 256.</td><td></td><td></td></tr>
<tr><td>[11]</td><td>The photos classified by type were handled using Matlab version 2016a software. The photos were then change to grayscale, then further changed into black and white using the im2bw command. The labelled photos were produced by the use the vislabels andbwlabel routines. Using image processing methods, the software made it easier to sort the different things in the pictures into groups.</td><td>The coffee beans utilised in the study were sourced from the Cavite State University in Indang, Cavite (National Coffee Research Development and Extension Center (NCRDEC)).. The coffee bean varietals were Libericam Robusta, and Excelsa. A total of 120 samples were collected for each type. The dataset included of 60 instances for training purposes and an additional 60 instances for data testing.</td><td>Decision Trees, Ensemble</td><td>
<table>
<tr><th colspan="2">Classifier</th><th>%</th></tr>
<tr><td rowspan="3">Decision Tree</td><td>Complex Tree</td><td>91.1</td></tr>
<tr><td>Medium Tree</td><td>91.1</td></tr>
<tr><td>Simple Tree</td><td>86.7</td></tr>
<tr><td rowspan="5">Ensemble</td><td>Boosted Trees</td><td>33.3</td></tr>
<tr><td>Bagged Trees</td><td>95.6</td></tr>
<tr><td>Subspace Discriminant</td><td>82.2</td></tr>
<tr><td>Subspace KNN</td><td>86.7</td></tr>
<tr><td>RUSBoosted Trees</td><td>33.3</td></tr>
</table></td></tr>
<tr><td>[26]</td><td>The researchers analyzed the NIR spectra using the PLS toolbox software program in Matlab (ver. 9.2, The Mathworks, Inc., Natick, USA). They determined the ideal count of Principal Components (PCs) to keep in the PCA model by analyzing the</td><td>he researchers gathered 191 pieces of unroasted coffee beans from different geographic regions for their examination. 88 coffee samples were sourced from countries in Centre-</td><td>NIR spectroscopy, multivariate data analysis</td><td>98.5 for Brazil species
98.7 for Honduras species
93.5 for India species
83.7% for Vietnam Species
100% for America-class Species</td></tr>
</table>

	matching scree plot. The classification models used were created using the Partial Least Square Discriminant Analysis (PLS-DA) technique.	South America, while 103 samples were grown in different Asian countries. The samples comprised both Robusta and Arabica coffee, which are the predominant species of coffee plants. The researchers selected these producing countries and coffee varietals based on their importance to the Italian coffee market.		96.5% for Asia-class Species
[27]	IP camera was linked to the training model. The video stream was processed frame by frame by segmenting coffee bean photos using image segmentation techniques. Segmented images were subsequently subjected to preprocessing and inputted into the training model for identification. The result displayed green frames to represent predicted good beans and red frames to represent predicted bad beans, facilitating immediate and precise evaluation of coffee bean quality.	A dataset consisting of 72,000 photos was created by employing data augmentation techniques. The dataset was evenly split into two categories: 36,000 photos representing high-quality beans and an equal amount portraying low-quality beans. Following that, a stochastic selection procedure designated 7,000 photos from each category, establishing a subset for subsequent	CNN	94.63% Accuracy

		examination. The remaining augmented data, which constituted the majority of the dataset, was used as the training data for the experiment. The original image was merged to a black background and subsequently adjusted to a final size of 180 × 180 pixels.		
[28]	F-1 Score, Precision, and Recall Score measures were put to conduct a detailed investigation of the models' efficacy and classification performance.	The dataset used for model training in this work was intentionally selected and organised for research objectives. A total of 1554 photos of coffee beans, specifically depicting Espresso, Kenya, and Starbucks Pike Place coffee varieties, were gathered using a specially designed technique. After collecting the data, we performed both model training and testing operations. The cross-validation technique was employed to assess the efficacy of the models.	CNN (Inception V3, VGG16, and VGG19)	SqueezeNet 87.3% Inception V3 81.4% VGG16, 78.2% VGG19 72.5%

[29]	Due of the unavailability of coffee bean images online, the researchers had to procure green coffee beans from a local coffee shop.	To maintain consistent ambient conditions for image capture, the camera was positioned at a fixed distance of 17.5 cm over the green coffee beans. By utilizing an Application Programming Interface (API), they established a uniform set of camera characteristics, guaranteeing that every photograph accurately depicted the original colors and resolutions. In order to enhance the visibility of the coffee beans, it incorporated several materials and colors into the background. To achieve the best outcome, a black card with an ultra-dark shade and short hair was chosen as the background while capturing the shot. This decision successfully reduced the impact of shadows caused by inconsistent lighting conditions, guaranteeing precise depiction	CNN	93.34% Accuracy

		and absorption of reflected light. The researchers conducted an extensive photoshoot, obtaining photographs of 1000 high-quality beans and 1000 low-quality beans.		
[30]	the coffee beans were arranged on A4 white paper to acquire precise photographs. The camera was set up with precise parameters: an aperture of F/16, an exposure length of 1/60 s, ISO 200, exposure compensation of 1.3, autofocus mode, and an image resolution of 4928 x 3264. The camera was positioned exactly one meter (1 m) above the surface of the bean. photographs were taken of both the front and posterior surfaces of the coffee beans. Three unique lighting equipment were utilized to optimize the photographic scene. The obtained photos were resized to dimensions of 32 × 32, 64 × 64, 128 × 128, and 256 × 256 pixels. A corresponding collection of black-and-white photographs with the same dimensions was created.	The coffee beans being examined are of the Arabica variety. Green coffee samples were collected with great care from local growers in Timor-Leste. The study specifically examines two discrete categories of unroasted coffee beans: Peaberry: These are single embryos that were fertilised inside coffee cherries, not the usual flat-sided pair that you find in normal coffee beans. Non-defective: A standard coffee cherry typically consists of two beans with flat surfaces. These beans, also known as 'flat beans,' are impeccable and devoid of any imperfections	CNN, SVM, and KNN	CNN: 99.70% VGG-16: 9.38% Linear SVM: 96.10% KNN: 93.84%
[31]	The study commenced	Arabica Civet	Logistic	

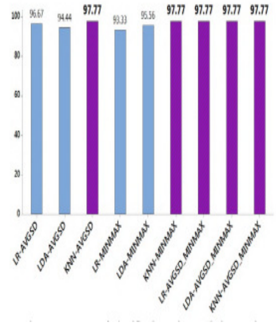
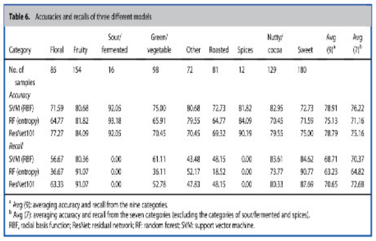
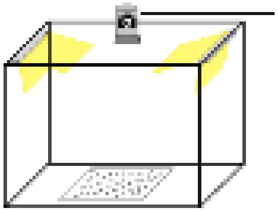
	upon the reception of a signal by the E-nose triggered by the scent of coffee. Subsequently, the Arduino translated the signal into data and delivered it to the computer.	coffee and Non-civet coffee. There are nine mixtures of data that are referred to as classes.	Regression (LR) Linear Discriminant Analysis (LDA) K-Nearest Neighbors (KNN) methods.	
[32]	The background or noise issues are addressed concurrently by mathematical processes. Thus, it was proposed that raw data be used as the input for both machine learning and deep learning models. To improve the effectiveness of the models and evaluate their ability to predict coffee flavor, the NIR coffee spectra were divided into training, validation, and testing sets using a random allocation, with an approximate ratio of 0.64:0.16:0.2. Both the models underwent training using the training set. The hyperparameters were determined through the utilization of the validation set. The evaluation of the constructed models was conducted using the testing dataset.	266 samples of Coffeaarabica, a type of arabica coffee, were bought from Blossom Valley International Co., Ltd in Taichung City, Taiwan. These samples were collected from 14 different nations.	NIR DCNN	

Table 6. Accuracies and recalls of three different models

Category	Floral	Fruity	Sour/ fermented	Green/ vegetable	Other	Roasted	Spices	Nutty/ cocoa	Sweet	Avg (9)[a]	Avg (7)[b]
No. of samples	85	154	16	98	72	81	12	129	180		
Accuracy											
SVM (RBF)	71.59	80.68	92.05	75.00	80.68	72.73	81.82	82.95	72.73	78.91	76.22
RF (entropy)	64.77	81.82	93.18	65.91	79.55	64.77	84.09	70.45	71.59	75.13	71.16
ResNet101	77.27	84.09	92.05	70.45	70.45	69.32	90.19	79.55	75.00	78.79	75.16
Recall											
SVM (RBF)	56.67	80.36	0.00	61.11	43.48	48.15	0.00	83.61	84.62	68.71	70.37
RF (entropy)	36.67	91.07	0.00	36.11	52.17	18.52	0.00	73.77	90.77	63.23	64.82
ResNet101	63.33	91.07	0.00	52.78	47.83	48.15	0.00	80.33	87.69	70.65	72.68

[a] Avg (9): averaging accuracy and recall from the nine categories.
[b] Avg (7): averaging accuracy and recall from the seven categories (excluding the categories of sour/fermented and spices).
RBF, radial basis function; ResNet: residual network; RF: random forest; SVM: support vector machine.

[33]	To systematically collect photographs of coffee samples, a wooden framework was erected to provide support for the camera. The camera was positioned above the coffee beans, which were spread out on a white piece of paper. This setup was used as an initial approach. 	The Serra and Alegre IFES (Instituto Federal de ciencia e tecnologia do Esp ˆ ´ırito Santo) campuses collaborated to acquire a collection of defective coffee beans, contaminants, and healthy grains from various sieves. All of the samples had already been sorted and categorized by experts.	Multilayer Perceptron neural network	94.10% Accuracy
[34]	The coffee beans were analysis with a time-domain THz spectroscopy instrument with a resolution of 0.0076 THz. Due to device limitations, only the absorbtion of THz spectrum data within the frequency range of 0.5–1.9 THz could be considered accurate.	96 Arabica coffee bean samples from three different geographical origins were evaluated. Among these, 30 samples of Kenya AA were obtained from Muchagara Estate in southern Kenya, 30 samples of Kilimanjaro were obtained Estate in Tanzania, from 36 samples were obtained from Baoshan, Yunnan. The selection of countries and species was based on their significance to the Chinese coffee	CNN, SVM	GA-SVM :75%. CNN: 90% accurate (specificity of 100% for Yunnan) (sensitivity of 100% for Kenya, Tanzania.)

		market.		

IV. CONCLUSIONS

This systematic review examines 14 diverse studies on the classification of coffee bean species, presenting a thorough understanding of the current state of machine learning applications in this field. The compilation of research not only demonstrates an extensive range of approaches but also emphasizes the adaptability of machine learning methods in handling the intricate complexities associated with the classification of coffee bean species. The investigation uncovers a diverse range of machine learning approaches utilized, including both conventional algorithms and advanced deep learning models. Every strategy possesses distinct advantages and considerations, which collectively contribute to the array of strategies aimed at precisely categorizing different kinds of coffee beans. The reported accuracies in this research illustrate the ongoing improvement and development of classification models. The analysis of the literature identifies certain areas that should be further investigated in the future. Models must be carefully evaluated to verify their robustness and capacity to generalize to diverse datasets of different sizes and compositions. As the field advances, it becomes increasingly clear that there is a growing need for a comprehensive grasp of the capabilities and constraints of various machine learning techniques. Researchers must collaborate to design optimal methods, improve current procedures, and investigate new approaches that utilize the combined potential of machine learning for the classification of coffee bean species.The findings also Indicates a significant pattern in the popularity of Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) as the most effective machine learning models for classifying coffee bean species. The combining of results from the 14 investigations highlights the impressive accomplishments attained by these advanced models, regularly surpassing previous machine learning methods achieving higher accuracies.

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