Linguistic and Philosophical Investigations
ISSN: 1841-2394, e-ISSN: 2471-0881
Vol 23 (1), 2024
pp. 2978-2986

Non-Invasive Fungicide Inspection Methodology Using Multispectral Imaging

Diego Alfonso Pelaez [1], Oscar Eduardo Gualdron Guerrero[2,3], Ivaldo Torres Chavez [2]

[1]Department of Mechatronics Engineering, University of Pamplona, Pamplona - Colombia
[2]Department of Electronic Engineering, University of Pamplona - Colombia.
[3]Agroinnova Research Group, Ernesto Schiefelbein Foundation, Bogotá, Colombia
{diego.pelaez, oscar.gualdron, ivaldo.torres}@unipamplona.edu.co

***Abstract*— The purpose of the current article is to show the development of a non-invasive multispectral imaging inspection methodology for the detection of fungicides on strawberry hulls. High quality images were captured using a Micasense RedEdge multispectral camera that captures images with a resolution of 1280 x 960 pixels in its five different spectral bands. The image acquisition process was performed in an environment controlling the stability of the light spectrum, the luminous intensity, the direction of the incident light and the focusing distance. To facilitate image preprocessing, a black background was used to optimize the segmentation process of the image of interest, facilitating the isolation and cropping of the object of interest to reduce the dimensionality of the images. The contamination of the samples with the selected fungicide was performed in the laboratory at 5 and 10 parts per million (ppm) to facilitate the validation of the classification results. The study included the combination of different spectral bands generating vegetation indices that allowed the correct classification between contaminated fruits using deep neural networks. Through the research it was possible to establish a methodology to identify the presence of pesticides in strawberries through ppm dilutions. In addition, an initial multispectral image acquisition system was proposed that minimizes the impact of external variables. Finally, a preprocessing and classification algorithm was developed, demonstrating that the crop growth index (CGI) allows detecting the chemical on strawberry surfaces.**

Keywords—Multispectral imaging, Image acquisition system, CGI index, Image Preprocessing, Pesticides.

I. INTRODUCTION

he world population for the year 2024 has presented a progressive deceleration, presenting figures as of today of approximately 8.2 billion people and is expected to reach approximately 10.3 billion by the year 2084, it is expected that by that point there will be a small decrease given the growing decline in the birth rate in many regions of the world [1]. This slowdown is the result of a significant drop in the global fertility rate, which has declined from 5 children per woman in the 1960s to 2.3 today [2]. This change is associated with factors such as access to education, especially among young women, and an increase in the availability of and access to contraceptive methods.

The change in global demographics directly affects agriculture and food production, due to the aging of the labor force, which is familiar with the production processes and the decrease of the active population in the field generates an increase in the need for technological solutions based on precision agriculture to compensate for the lack of workers in production. Other solutions that have become popular in agriculture have been the use of pesticides and chemicals that contribute directly to the control of pests and diseases, facilitating phytosanitary care.

Food security has been a constant concern for humanity due to its fundamental role in the survival and stability of societies, so much so that it is directly aligned with one of the Sustainable Development Goals (SDG) of the UN, particularly SDG 2: "Zero Hunger". This goal seeks to eradicate hunger and ensure access to safe, nutritious and sufficient food for all people.

The growth of the world's population is driving increased demand for food. Food security means ensuring that all people have access, physically, economically and socially, to an adequate amount of safe, nutritious and healthy food to meet their dietary needs and lead active and healthy lives. This requires the creation of resilient and sustainable food systems that can supply a growing population without damaging natural resources and the environment. Advanced agricultural technologies play a key role in improving productivity and efficiency in food production, thus helping to address global challenges in food production. It is also essential to reduce inequalities in access so that all people, regardless of their socioeconomic situation or location, can meet their food needs in a dignified and sustainable manner.

The use of pesticides together with the development of new agricultural technologies has been key to increasing food production globally. Tools such as precision agriculture and genetically modified crops represent innovations that enable more efficient management of resources such as water, fertilizers and soil, which enhances both productivity and efficiency in agricultural production. With proper and responsible use, pesticides protect crops against pests and diseases that can reduce crop yields and quality. This not only ensures greater food availability, but also ensures more uniform and higher quality production, with crops that are more resistant to losses due to environmental or biological factors. In response to the growing food needs of an expanding population, modern agriculture relies on the strategic use of pesticides and technologies to contribute to food security on a global scale.

The need to increase production forcing farmers to use large amounts of pesticides to control pests and diseases. This produces environmental and consumer health impacts and increased pest resistance to pesticides as a relevant long-term effect. Part of the pesticides remain on the surface of consumable products, which is harmful to health and makes it necessary to develop tools for their monitoring [3]. A wide variety of pesticides are available on the market and can be purchased by most producers, in some countries without any regulation on the amount of input applied per hectare or the type of chemical compounds, which allows the excessive use of these chemicals, so much so that in the last 20 years their use has increased by 360% while soil use has only increased by 29% [4], [5].

Fruits are the agricultural products that have experienced the greatest increase in production and exports, but even so, they do not exceed the land extensions destined to products such as coffee, bananas and sugarcane, which have an average of 372,038 hectares cultivated per product. These have an average of 372,038 hectares cultivated per product, unlike products such as oranges, mango or lemons, which do not exceed 33,213 hectares, which is why the list of chemicals assigned to their phytosanitary care is not large, resulting in a low interest in research that allows the characterization and quantification of pesticides in fruits [6]. It is common to find agricultural products with pesticide residues in their state of commercialization, which generates greater concern in fruits because they are more consumed raw or without preparation. For this reason, it is necessary to have technologies that allow quality inspections of the products so that an efficient control of the presence of these toxicants in the final product can be carried out [7].

Gas chromatography is currently the most widely used analytical technique for the qualitative and quantitative detection of pesticide residues in any biological material due to its sensitivity [8], [9], [10], [11]. Its major drawback is its high cost per sample analyzed since it is difficult to calibrate and operate, it is a slow process and needs specialized personnel to perform the above-mentioned activities to obtain a detection trace [12]. In addition, we cannot leave behind the fact that it is a destructive test and that the analyzed material cannot be used later. On the other hand, the electronic nose is a device that simulates the sense of human perception of odors by means of gases; it is composed of arrays of sensors sensitive to different gases or specific volatiles [13], [14]. It is currently used in applications that provide solutions to the most common problems presented by gas chromatography, although its applications are still in laboratory conditions, and present difficulties in the portability for the acquisition of information in the field [11], [14], [15].

It is expected that the new techniques for detecting pesticides in fruit will be easy to implement, low cost in the technology used in operation, and that their use will not be invasive or destructive. Artificial vision is a non-invasive methodology that, by means of conventional high-resolution cameras, allows acquiring relevant information on the surface aspects of plants. This data can be used by classification algorithms to characterize and identify their morphology and anomalies [16], [17]. RGB cameras have a great spectral limitation in the same way as human sight, when trying to identify chemical or physiological interactions, since it does not allow to observe the interactions of waves with objects in wavelengths outside the visible light spectrum, being this a very narrow range, which does not allow to capture relevant phenomena in fruits or plant material [18], [19].

In this new context, it is proposed to implement multispectral cameras to optimize agricultural productivity and reduce the consumption of resources such as water, fertilizers and pesticides. The main objective of this article is to present a methodology to detect contaminants on the surface of strawberries by means of artificial vision, using multispectral images. This technique, framed in precision agriculture, not only improves crop efficiency, but also makes it possible to identify the presence of unwanted chemicals in fruits, thus ensuring greater food safety and quality of the final product for the consumer, while minimizing the environmental impact [20].

Multispectral cameras use five spectral bands and RGB images, which are part of the spectrum not visible to the human eye, to differentiate plants and objects based on their spectral characteristics, as illustrated in Fig. 1. In projects such as cotton plant recognition, these technologies can identify areas conducive to cotton boll weevils by analyzing bimodal histograms specific to cotton and other vegetation and soil types [21]. They are also applied to distinguish tea plant varieties by capturing and analyzing properties such as hue, saturation, textures and spectral vegetation indices. This process involves image registration, calibration, segmentation, data extraction and information fusion to improve crop management and optimize resource use [22].

Fig. 1. Multispectral camera MicaSense RedEdge.

The principle of operation of multispectral imaging is based on sensors that capture solar radiation. These waves pass through the atmosphere and interact with the earth's surface [23]. The interaction between radiation and objects is recorded and analyzed for different applications and is manifested as follows: a part of the radiation incident on the object is reflected (reflectance); another part is transmitted through it (transmittance); and a portion is absorbed (absorbance), being subsequently emitted in the form of heat [24], [25].

The types of electromagnetic radiation (EMR) are organized according to their wavelength or frequency, and the graphical representation of their distribution is called the electromagnetic spectrum. Groupings of EMR with similar characteristics are called bands or segments, the main ones of interest for remote sensing being visible, infrared (IR) and microwave. Multispectral imaging cameras are equipped with an interference filter mounted in front of the lens, designed to block or transmit specific wavelengths. Unlike RGB cameras, multispectral sensors offer more useful wavelength bands in the visible and near infrared (NIR) regions, allowing detailed information to be captured in these areas of the spectrum [26].

Multispectral images combined with deep machine learning have proven to be a viable option for the identification and characterization of pesticide concentrations in different fruits or agricultural products, leaving behind different restrictions [27].

The main objective of machine learning is pattern recognition. By acquiring multispectral images and applying this type of algorithm, applications such as determining the agronomic conditions of a crop, enabling pest control and quantifying different types of stress in crops can be achieved [28]. One of the most promising techniques based on machine learning are deep neural networks (Deep learning) with which it is also possible to estimate the yield of production of different types of crops, acquiring information by means of an unmanned aerial vehicle [29], RGB sensors [30], sensors in different wavelengths and low-cost thermal camera allowing to obtain valuable information for phenotyping and crop management [31], after the application of data processing algorithms [32].

The application of machine learning techniques is an important part of the research shown in this article since it is used to discern patterns and classify images of fruits that harbor fungicide residues and those that are free of such compounds. This tool focuses on analyzing in detail the characteristics present in the multispectral images, which will enable differentiation. The ability of these techniques to identify spectral subtleties will allow for a highly effective and specific detection system, thus providing a reliable method to ensure the characterization of agricultural products [33].

II. Methodology

The research employed a detailed methodological approach, illustrated in Fig. 2, which ensures a systematic and rigorous process for the acquisition and processing of multispectral images to identify fungicide residues on the surface of strawberries. From pesticide selection to the creation of a structured database and image preprocessing, this method covers all essential aspects. This process has been carefully planned to obtain high quality data. In the initial phase of the study, a detailed review of different types of pesticides is carried out to select the one to be used in the intentional contamination of strawberries. During this process, key factors are considered, such as the efficacy of the pesticide for the purpose of the experiment and its influence on multispectral imaging. Pesticide concentrations in parts per million (ppm) are also evaluated to ensure that they meet the limits stipulated by international standards. The objective is to identify the optimal way to apply the pesticide, achieving a controlled contamination of the strawberries, which will allow accurate analysis of their behavior and detectable residues using multispectral imaging techniques. After choosing the contaminant, information is gathered on factors that may affect the quality and accuracy of multispectral images used to detect chemical residues on the surface of the strawberries. This process involves considering variables such as illumination, focal length, and other environmental factors that can affect the ability to accurately detect the presence of chemical debris. These elements are crucial to ensure the reliability of the images obtained.

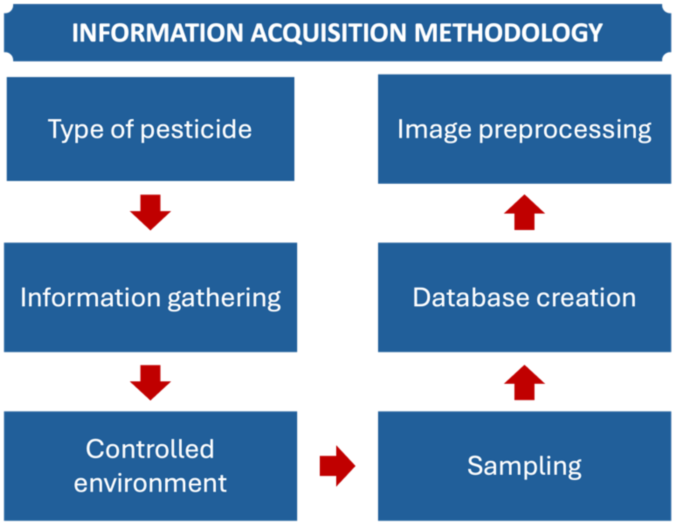

Fig. 2. Methodology for the acquisition of multispectral images of contaminated fruits.

A controlled environment is established considering factors such as the distance between the multispectral camera and the object, the light source and the background contrast in the images. This configuration is based on previous studies to ensure optimal conditions for multispectral imaging. This achieves an accurate and uniform acquisition of the data needed for the analysis, minimizing external influences that may affect the quality of the images [34].

During the sampling phase, multispectral images are acquired with a specialized MicaSense camera, model RedEdge, designed to capture a variety of spectral bands: red, green, blue, near infrared and red edge [35]. These bands provide a wealth of information about the spectral properties of the strawberries and the pesticide residues on their surface.

After capture, the images are organized, stored and labeled in a structured database designed to facilitate the training and development of deep learning neural network algorithms. During the preprocessing phase, various operations are performed to improve the quality and utility of the images, including segmentation methods to distinguish burrs from other elements in the photos and precise cropping to focus on areas of interest. Size reduction is also performed to optimize data handling and analysis. These preprocessing techniques are fundamental to prepare multispectral images, allowing the application of combination and manipulation techniques of the different spectral bands captured, and thus generate specific vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and the Chlorophyll Green Index (CGI) [36].

III. RESULTS AND ANALYSIS

This section presents the most relevant results of the implementation of the designed methodology, which has allowed the creation of a reliable database to develop a technique for the identification of pesticides on the surface of fruits. In an initial phase, the methodology was applied to strawberries due to the need to protect this fruit with different chemical products to comply with the quality standards required for its commercialization. In addition, the findings on the different variables studied will be shared, offering a first approach towards the future development of a prototype for the acquisition of multispectral images in fruits.

A. *Pesticide Identification*

Field research was conducted with visits to several local farmers to collect data on their practices and experiences with different chemicals. The main objective of this research was to identify the appropriate pesticide for the project, considering the types of chemicals available and their specific agricultural applications. In this process, three main categories of products were recognized: fungicides, insecticides and acaricides, each focused on combating various crop pests and diseases.

Fungicides are used to prevent and control fungi and diseases; some of these products are applied directly to the fruit to prevent Botrytis cinerea, a fungus that causes fruit rot. To ensure the correct application on strawberries, specialized agronomists were consulted and recommended the use of the product Anker because of its suitability for the objectives of the project. To ensure the presence of the product on the strawberries, even after the dilutions necessary to reach specific concentrations in ppm, application by immersion was recommended.

As shown in Fig. 3, a dilution of the chemical solution was carried out to simulate ppm levels typical of commercially available strawberries. For the study, two concentrations were established: 5 ppm and 10 ppm.

Fig. 3. Dilution by ppm of the fungicide.

B. *Creation of a Controlled Environment*

Based on the knowledge of the behavior of light and reflectance as a physical magnitude useful for comparing the electromagnetic radiation that strikes the surface of objects according to their colors, we chose to create a matte black board, with dimensions of 40 cm by 40 cm. This size allows minimizing any unwanted light that, at the time of capturing the images, could influence the desired results.

A special support for the multispectral camera was designed using modeling software and 3D printing techniques, with specifications that allow it to be fixed in a single position. In addition, an elevated support system was constructed that allows the camera to be placed at two different distances from the table and the fruit: 14.5 cm and 35.5 cm. This design seeks to observe if there is a significant difference in the data captured at both distances, considering that these types of cameras are usually used at great heights, between 60 and 120 meters above the ground. An incandescent bulb was also included to provide an artificial light source.

Multispectral cameras operate with a voltage range between 4 and 16 volts and a maximum current of 4A, so it was necessary to find a suitable power supply, which had the corresponding connector and allowed the regulation of these specifications. To connect it to the camera, XT30 connectors and a jack-type power connector were used. As for the artificial light source, a 100W incandescent bulb was used, capable of producing approximately 1600 lumens.

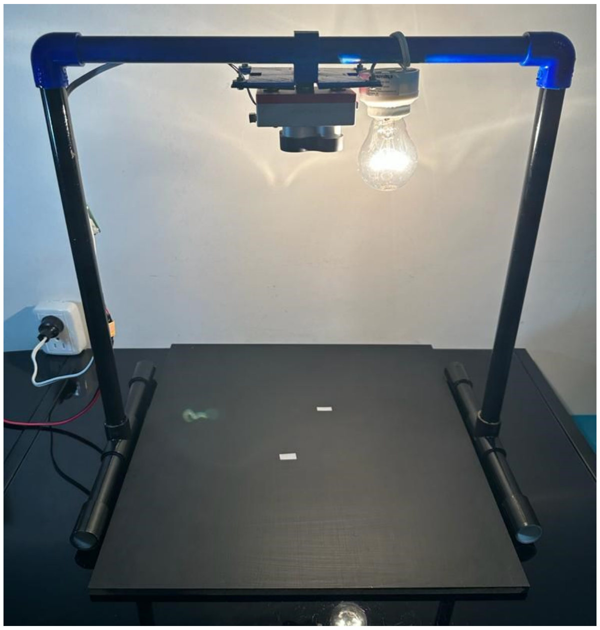

Fig. 4. Initial Prototype of Multispectral Image Acquisition System.

Considering the specifications previously described, the system shown in Fig. 4 was assembled, which allows for adjustments as necessary to ensure correct data capture.

C. Multispectral Image Acquisition

First, photographs were taken of the burs without the chemical applied, using both heights previously established. This was done because the size of each pixel represented approximately 62 mm^2 of surface area at the highest height and 15 mm^2 at the lowest, so that each pixel captured the maximum amount of information. Subsequently, a second phase of data capture was performed in which all the burs were treated with the chemical before taking the new photographs.

This procedure was also repeated using artificial light. For this, the images were captured in a completely dark environment, ensuring that the only light source was the incandescent bulb. In this way, it was ensured that the light reflected by the fruit was not altered, achieving an accurate capture of the visual information with the camera.

D. Database Creation

All images were transferred to the computer and organized based on the different capture conditions. They were grouped into two main categories: those taken under natural light and those captured with artificial light. Each category was further divided into four sub-conditions, according to the presence or absence of pesticides and the distance at which each image was taken.

For the images with artificial light, a total of 1800 was captured: 485 close-up images without pesticide, 425 close-up images with pesticide, 410 distant images with pesticide, and 480 distant images without pesticide. For the images with natural light, 1750 photos were recorded: 420 close-ups with pesticide, 435 close-up without pesticide, 410 distant with pesticide, and 485 distant without pesticide.

.

E. Multispectral Image Preprocessing

With a balanced set of images that include pesticides and those that do not, we proceed to identify and apply the technique that is theoretically most effective for detecting residues of the applied fungicide. Initially, several images are processed to generate an NDVI (Normalized Difference Vegetation Index) representation using the red and near-infrared bands (as shown in Fig. 5). This procedure is primarily conducted for reference purposes, facilitating the comparison between the NDVI results and another technique, the CGI (Color Gradient Index), which has demonstrated superior results in previous trials. By comparing these two approaches, we aim to confirm the capability of CGI to accurately identify fungicide residues, thereby ensuring a thorough and comprehensive analysis. The reference NDVI images serve as a standard for evaluating the efficacy of the CGI, highlighting its potential advantages and providing a clearer understanding of its application in real-world scenarios. This comparative approach reinforces our commitment to adopting the most effective techniques available, ensuring the accuracy and reliability of our findings in detecting pesticide residues.

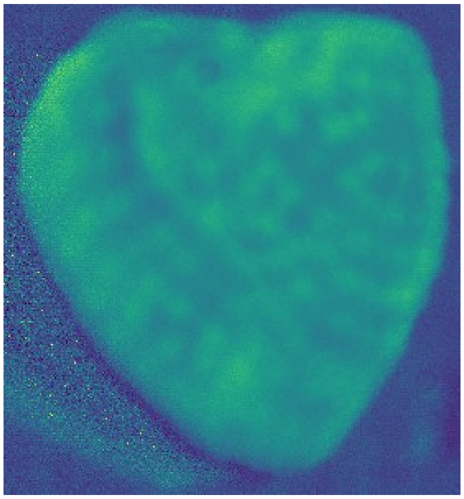

Fig. 5. Image processed with NDVI technique.

During the preprocessing phase, the images to be utilized in the proposed method are selected. For the CGI, the images ending in 2.tif and 4.tif are chosen, as illustrated in Fig. 6. These images undergo a dimensionality reduction process and are subsequently converted into numpy arrays for analysis.

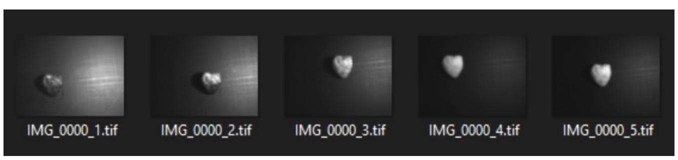

Fig. 6. Images in TIFF format across different channels of the same sample.

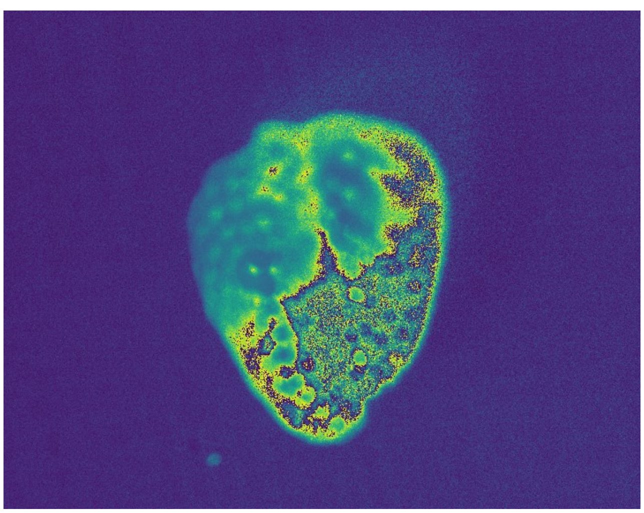

Fig. 7. Color application to the CGI image for better data comprehension.

With the array, it's possible to perform normalization and try to establish the brightest points as bright as possible and the darkest points as black. The numpy arrays are combined into one and converted into a new image from that combined matrix. The CGI is applied to this image by converting it back into a matrix, extracting the green and near-infrared channels to apply the technique. The colors are scaled to the range [0, 255] and a new image is created. The goal is for this technique to show significant variations on the surface of each strawberry. A new normalization is applied and then it's colorized to enhance details that might be overlooked in a grayscale image. The result is shown in Fig. 7.

F. Implementation of convolutional neural networks

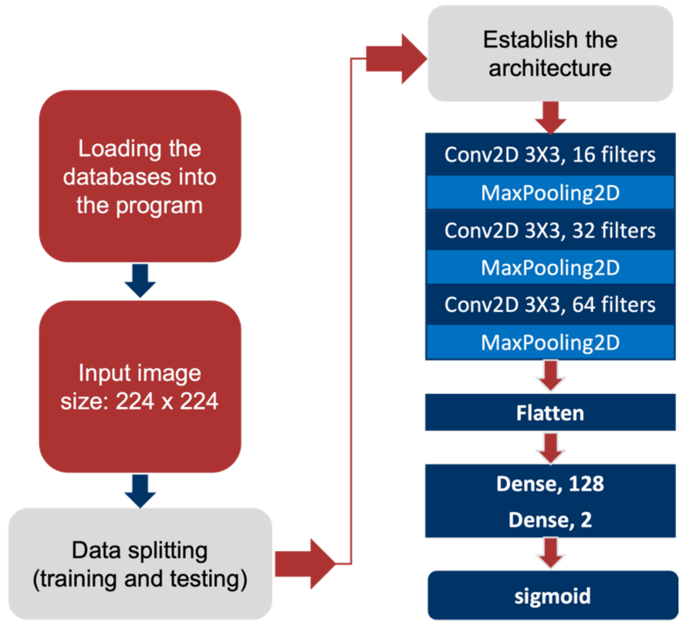

Fig. 8. implementation of convolutional neural network architecture (CNN).

The implementation of a convolutional neural network (CNN) model for analyzing multispectral images of pesticide-contaminated strawberries is illustrated in the flowchart shown in Figure 8. Initially, the program requires loading the necessary databases before importing the images intended for training and evaluating the model. To ensure uniformity in input, these images are resized to a standard dimension of 224 × 224 pixels. Subsequently, the data is divided into training and test sets to allow for parameter adjustment and performance evaluation of the model.

The architecture of the neural network is built upon an initial set of convolutional layers followed by max pooling layers. The first convolutional layer (Conv2D) utilizes filters sized 3x3, with a total of 16 filters to extract essential features from the images. This is succeeded by a max pooling layer (MaxPooling2D), which reduces the dimensionality of the extracted features. The process is repeated with additional convolutional layers, increasing the filter count to 32 and then to 64, each followed by a max pooling layer. This arrangement facilitates the extraction of progressively more complex and refined features from the images.

To ready the extracted features for the dense layers, a Flatten layer is used to convert them into a one-dimensional vector at the end of the process. The first dense layer (Dense), comprising 128 neurons, analyzes the flattened features and learns complex patterns. The second dense layer consists of two neurons, which is suitable for binary output, indicating the presence or absence of pesticides. The outputs from the dense layer are converted into probabilities through the sigmoid activation layer, facilitating binary classification. This methodological approach demonstrates the effectiveness of the proposed procedure by enabling accurate detection of chemical residues in strawberries.

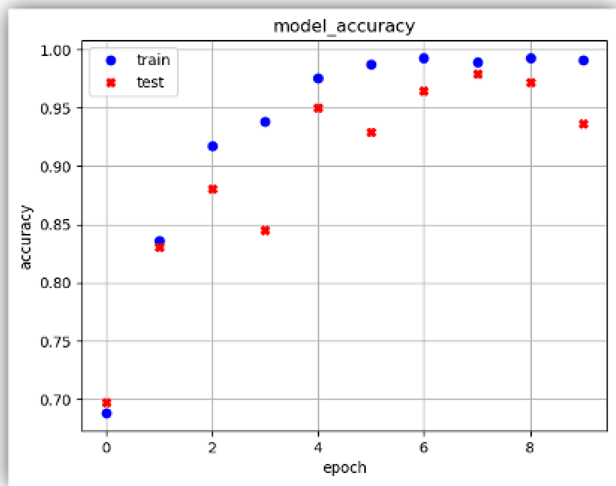

Fig. 9. model accuracy during training and testing of a CNN.

A CNN is trained and evaluated using multispectral images of strawberries contaminated with pesticides, with the model's accuracy presented graphically in Fig. 9. The vertical axis represents the accuracy achieved, while the horizontal axis denotes the training iterations. Throughout the epochs, a steady increase in model accuracy is observed for both the training and test sets. In the initial epochs, accuracy rises sharply, indicating that the model is effectively capturing essential features from the images. From the fifth epoch onward, the accuracy on the training set levels off at nearly 100%, demonstrating that the model has learned to classify almost all training images accurately.

In contrast, the accuracy on the test set reaches a maximum of approximately 97%, followed by minor fluctuations. This difference highlights that, despite the model's strong generalization capabilities, its performance may vary when evaluating new images. The expected high accuracy on the training set and the slight decline in the test set accuracy are attributed to the variability of unseen data encountered during training. This pattern is commonly seen in well-trained CNN models.

CONCLUSIONS

The study facilitated a comparison of various pesticide types, ultimately identifying the fungicide Anker as the most suitable choice for contaminating the samples due to its prevalent use in agriculture. Furthermore, a method was developed to monitor pesticide levels in strawberries by creating various dilutions in ppm. An initial design for a multispectral image acquisition system was introduced, aimed at ensuring effective information capture while reducing the impact of external variables that could compromise sampling quality. Additionally, a preprocessing algorithm was crafted to apply techniques for combining spectral bands, with preliminary results indicating that the CGI index effectively reveals the presence of the selected chemical on strawberry surfaces.

The effectiveness of employing a CNN model for analyzing multispectral images of pesticide-contaminated strawberries has been confirmed. Through a meticulous training process and a carefully designed architecture, the model achieved a high classification accuracy of 97%. Its ability to generalize is evidenced by the stable accuracy observed in the training set and the minor fluctuations in the test set. These results underscore the potential applicability of the proposed method in real-world scenarios within the food industry, validating its effectiveness in detecting chemical residues in strawberries.

REFERENCES

[1] A. Braverman-Bronstein *et al.*, "Gender inequality, women's empowerment, and adolescent birth rates in 363 Latin American cities," *Soc Sci Med*, vol. 317, p. 115566, 2023, doi: https://doi.org/10.1016/j.socscimed.2022.115566.

[2] M. Swain, M. Miller, C. Cannella, S. Doe, L. Petersen, and J. Bensenhaver, "A Retrospective Study of Fertility Counseling and Preservation Rates for Women of Reproductive Age With Breast Care After Integrating a Fertility Specialist Into a Multidisciplinary Tumor Board," *Clin Breast Cancer*, 2024, doi: https://doi.org/10.1016/j.clbc.2024.09.003.

[3] S. Sun, R. Hu, and C. Zhang, "Pest control practices, information sources, and correct pesticide use: Evidence from rice production in China," *Ecol Indic*, vol. 129, p. 107895, 2021, doi: https://doi.org/10.1016/j.ecolind.2021.107895.

[4] U. Nations, "Food Production Must Double by 2050 to Meet Demand from World's Growing Population, Innovative Strategies Needed to Combat Hunger, Experts Tell Second Committee," in *Sixty-fourth General Assembly Second Committee*, 2010.

[5] T. A. Naji, M. A. Teka, and E. A. Alemu, "The impact of watershed on household food security: A comparative analysis," *J Agric Food Res*, vol. 15, p. 100954, 2024, doi: https://doi.org/10.1016/j.jafr.2023.100954.

[6] D. A. Varela-Martínez, M. Á. González-Curbelo, J. González-Sálamo, and J. Hernández-Borges, "High-throughput analysis of pesticides in minor tropical fruits from Colombia," *Food Chem*, vol. 280, pp. 221–230, 2019, doi: https://doi.org/10.1016/j.foodchem.2018.12.045.

[7] G. Qin *et al.*, "Risk assessment of fungicide pesticide residues in vegetables and fruits in the mid-western region of China," *Journal of Food Composition and*

Analysis, vol. 95, p. 103663, 2021, doi: https://doi.org/10.1016/j.jfca.2020.103663.

[8] P. Biparva, S. Gorji, and E. Hedayati, "Promoted reaction microextraction for determining pesticide residues in environmental water samples using gas chromatography-mass spectrometry," *J Chromatogr A*, vol. 1612, p. 460639, 2020, doi: https://doi.org/10.1016/j.chroma.2019.460639.

[9] H. Hopfer, "Analytical Methods: Gas Chromatography," in *Reference Module in Food Science*, Elsevier, 2020. doi: https://doi.org/10.1016/B978-0-12-818766-1.00024-6.

[10] E. Rutkowska, B. Łozowicka, and P. Kaczyński, "Compensation of matrix effects in seed matrices followed by gas chromatography-tandem mass spectrometry analysis of pesticide residues," *J Chromatogr A*, vol. 1614, p. 460738, 2020, doi: https://doi.org/10.1016/j.chroma.2019.460738.

[11] A. Ferracane, M. Zoccali, F. Cacciola, T. M. G. Salerno, P. Q. Tranchida, and L. Mondello, "Determination of multi-pesticide residues in vegetable products using a 'reduced-scale' Quechers method and flow-modulated comprehensive two-dimensional gas chromatography-triple quadrupole mass spectrometry," *J Chromatogr A*, vol. 1645, p. 462126, 2021, doi: https://doi.org/10.1016/j.chroma.2021.462126.

[12] J. K. Carrillo Gómez, C. M. Duran Acevedo, and R. O. Garcia Rico, "Discriminación de bacterias en agua potable a través de una nariz electrónica y un equipo de extracción de volátiles," *REVISTA COLOMBIANA DE TECNOLOGIAS DE AVANZADA (RCTA)*, vol. 1, no. 33, pp. 155–165, Jan. 2019, doi: 10.24054/rcta.v1i33.99.

[13] D.-A. C. Manuel, G.-G. O. Eduardo, and H.-O. Mariela, "Nariz electrónica para determinar el índice de madurez del tomate de árbol (Cyphomandra Betacea Sendt)," *Ingeniería, Investigación y Tecnología*, vol. 15, no. 3, pp. 351–362, 2014, doi: https://doi.org/10.1016/S1405-7743(14)70346-4.

[14] M. A. Rivera, O. E. Gualdron, and D. A. Pelaez, "Quantification of volatile compounds present in organophosphorus compounds, through the variation of the electrostatic potential in chemical-resistive sensors," *J Phys Conf Ser*, vol. 1704, p. 12015, Nov. 2020, doi: 10.1088/1742-6596/1704/1/012015.

[15] O. Golge, S. Cinpolat, and B. Kabak, "Quantification of pesticide residues in gherkins by liquid and gas chromatography coupled to tandem mass spectrometry," *Journal of Food Composition and Analysis*, vol. 96, p. 103755, 2021, doi: https://doi.org/10.1016/j.jfca.2020.103755.

[16] J. A. Gómez, H. Yulady Jaramillo, and L. A. Coronel Rojas, "Sistema para detección de fallos críticos en tuberías horizontales," *REVISTA COLOMBIANA DE TECNOLOGIAS DE AVANZADA (RCTA)*, vol. 1, no. 35, pp. 44–51, Feb. 2020, doi: 10.24054/rcta.v1i35.41.

[17] G. Dhanush, N. Khatri, S. Kumar, and P. K. Shukla, "A comprehensive review of machine vision systems and artificial intelligence algorithms for the detection and harvesting of agricultural produce," *Sci Afr*, vol. 21, p. e01798, 2023, doi: https://doi.org/10.1016/j.sciaf.2023.e01798.

[18] H. Liu and J. S. Chahl, "Proximal detecting invertebrate pests on crops using a deep residual convolutional neural network trained by virtual images," *Artificial Intelligence in Agriculture*, vol. 5, pp. 13–23, 2021, doi: https://doi.org/10.1016/j.aiia.2021.01.003.

[19] F. R. Cuesta Quintero, L. A. Coronel Rojas, D. Rico Bautista, E. Barrientos Avendaño, O. J. Montañez vergel, and C. M. Páez Noriega, "Sistema de detección de intrusos a través de una red honeynet para entornos de red cableada sobre IPv6," *REVISTA COLOMBIANA DE TECNOLOGIAS DE AVANZADA (RCTA)*, vol. 1, no. 33, pp. 104–113, Jan. 2019, doi: 10.24054/rcta.v1i33.92.

[20] A. Rahiche, R. Hedjam, S. Al-maadeed, and M. Cheriet, "Historical documents dating using multispectral imaging and ordinal classification," *J Cult Herit*, vol. 45, pp. 71–80, Sep. 2020, doi: 10.1016/J.CULHER.2020.01.012.

[21] D. Walshe, D. McInerney, R. Van De Kerchove, C. Goyens, P. Balaji, and K. A. Byrne, "Detecting nutrient deficiency in spruce forests using multispectral satellite imagery," *International Journal of Applied Earth Observation and Geoinformation*, vol. 86, p. 101975, 2020, doi: https://doi.org/10.1016/j.jag.2019.101975.

[22] B. Wang *et al.*, "Evaluation of insulator aging status based on multispectral imaging optimized by hyperspectral analysis," *Measurement*, vol. 205, p. 112058, Dec. 2022, doi: 10.1016/J.MEASUREMENT.2022.112058.

[23] R. Tanabe, T. Matsui, and T. S. T. Tanaka, "Winter wheat yield prediction using convolutional neural networks and UAV-based multispectral imagery," *Field Crops Res*, vol. 291, p. 108786, 2023, doi: https://doi.org/10.1016/j.fcr.2022.108786.

[24] I. Blekanov, A. Molin, D. Zhang, E. Mitrofanov, O. Mitrofanova, and Y. Li, "Monitoring of grain crops nitrogen status from uav multispectral images coupled with deep learning approaches," *Comput Electron Agric*, vol. 212, p. 108047, 2023, doi: https://doi.org/10.1016/j.compag.2023.108047.

[25] D. Pérez García, F. García Reina, and D. Hernández Eduardo, "Disminución de las pérdidas de energía eléctrica por distribución usando una tecnología novedosa de mediciones y control para la toma de decisiones," *REVISTA COLOMBIANA DE TECNOLOGIAS DE AVANZADA (RCTA)*, vol. 2, no. 34, pp. 144–150, Jul. 2019, doi: 10.24054/rcta.v2i34.75.

[26] M. Balbis Morejón, F. García Reina, J. J. Cabello Eras, and V. Sousa Santos, "Caracterización energética del

funcionamiento de un equipo de aire acondicionado en un local dado," *REVISTA COLOMBIANA DE TECNOLOGIAS DE AVANZADA (RCTA)*, vol. 2, no. 34, pp. 71–76, Jul. 2019, doi: 10.24054/rcta.v2i34.65.
[27] G. Modica, G. Messina, G. De Luca, V. Fiozzo, and S. Praticò, "Monitoring the vegetation vigor in heterogeneous citrus and olive orchards. A multiscale object-based approach to extract trees' crowns from UAV multispectral imagery," *Comput Electron Agric*, vol. 175, p. 105500, 2020, doi: https://doi.org/10.1016/j.compag.2020.105500.
[28] F. H. Juwono, W. K. Wong, S. Verma, N. Shekhawat, B. A. Lease, and C. Apriono, "Machine learning for weed–plant discrimination in agriculture 5.0: An in-depth review," *Artificial Intelligence in Agriculture*, vol. 10, pp. 13–25, 2023, doi: https://doi.org/10.1016/j.aiia.2023.09.002.
[29] B. Jiang *et al.*, "Fusion of machine vision technology and AlexNet-CNNs deep learning network for the detection of postharvest apple pesticide residues," *Artificial Intelligence in Agriculture*, vol. 1, pp. 1–8, 2019, doi: https://doi.org/10.1016/j.aiia.2019.02.001.
[30] C. Davidson, V. Jaganathan, A. N. Sivakumar, J. M. P. Czarnecki, and G. Chowdhary, "NDVI/NDRE prediction from standard RGB aerial imagery using deep learning," *Comput Electron Agric*, vol. 203, p. 107396, Dec. 2022, doi: 10.1016/J.COMPAG.2022.107396.
[31] J. de Abreu Fontes, M. J. Anzanello, J. B. G. Brito, G. B. Bucco, F. S. Fogliatto, and F. do P. Puglia, "Combining wavelength importance ranking to the random forest classifier to analyze multiclass spectral data," *Forensic Sci Int*, vol. 328, p. 110998, Nov. 2021, doi: 10.1016/J.FORSCIINT.2021.110998.
[32] M. Sharma, N. Mittal, A. Mishra, and A. Gupta, "An efficient approach for load forecasting in agricultural sector using machine learning," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 6, p. 100337, 2023, doi: https://doi.org/10.1016/j.prime.2023.100337.
[33] T. Talaviya, D. Shah, N. Patel, H. Yagnik, and M. Shah, "Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides," *Artificial Intelligence in Agriculture*, vol. 4, pp. 58–73, 2020, doi: https://doi.org/10.1016/j.aiia.2020.04.002.
[34] D. Saha and A. Manickavasagan, "Machine learning techniques for analysis of hyperspectral images to determine quality of food products: A review," *Curr Res Food Sci*, vol. 4, pp. 28–44, 2021, doi: https://doi.org/10.1016/j.crfs.2021.01.002.
[35] D. A. Pelaez, O. E. Gualdron, and L. Castellanos, "Analysis of the intensity of electromagnetic radiation for the estimation of vegetation cover," *J Phys Conf Ser*, vol. 1704, p. 12008, Nov. 2020, doi: 10.1088/1742-6596/1704/1/012008.
[36] L. Castro Sardiña, G. Irisarri, and M. Texeira, "Climate factors rather than human activities controlled NDVI trends across wet meadow areas in the Andes Centrales of Argentina," *J Arid Environ*, vol. 214, p. 104983, Jul. 2023, doi: 10.1016/J.JARIDENV.2023.104983.