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Low-cost VIS/NIR range hand-held and portable photospectrometer and evaluation of machine learning algorithms for classification performance

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ABSTRACT

In this study, the electronic design of a low-cost and portable spectrophotometer device capable of analyzing in the visible-near infrared region was established. The design of C#.NET-based user-friendly device control software and the development of machine learning algorithms for data classification as well as the comparison of the results were presented. When the spectrophotometer design and implementation studies are reviewed in the literature, two groups of subjects become prominent: (i) a new device fabrication, (ii) solution approaches to current problems by combining commercial portable spectrometer systems and devices with artificial intelligence applications. This work encompasses both groups, and a supportive approach has been followed on how to transform the theoretical knowledge into practice in device development and supportive software with the help of machine learning approaches from design to production. Three commercial spectral sensors, each with six photodiode arrays, were adopted in the spectrophotometer. Thus, 18 features belonging to each sample were acquired in the optical spectral region in the 410 nm to 940 nm band range. The spectral analyses were conducted with 9 different food types of powder or flake structures. A Support Vector Machines (SVM) and Convolutional Neural Network (CNN) approaches were employed for data classification. As a result, SVM and CNN achieved 97% and 95% accuracies, respectively. Moreover, we provided the spectral measurement data, the electronic circuit designs, the API files containing the artificial intelligence algorithms and the graphical user interface (GUI).

1. Introduction

It is a matter which all humanity agrees that the way to a healthy and quality continuity of life is not only possible with a balanced diet, but mainly through eating reliable foods. In addition to positively affect human health with the nutrients they contain, foods threaten human health by opening the door to diseases and even deaths due to the dysfunctional contents they can carry. While urbanization and the increase in the population of cities lead to a great demand for food and ready-to-eat products in our modern cities, this food supply often paves the way for fraud [1–4]. Therefore, the food must be inspected throughout the entire process, from the raw material where production begins, until it comes to our table. Interest in fast, reliable and environmentally friendly technologies in quality and correct food consumption, production stage or analysis of food is increasing, and accordingly, various technologies alternative to traditional methods are being developed [5,3,6]. Food counterfeiting is understood by neglecting its ingredients and substituting cheap food ingredients. To detect fraud, the need for reliable analytical methods and devices in all transformation stages of food from raw material to final product has enabled researchers to focus on this area. The analyzes are mainly allergen, physical, chemical, material, additive-residue, microbiological, metal-mineral and toxin analyzes [3,7,8]. Since the absorbance spectrum of the substances is specific to the relevant substance, their evaluation as chemical fingerprints is an important factor that increases the success power of optical analysis. More than 90% of the food analyzers performed today are carried out under laboratory conditions and with traditional methods. While rapid diagnostic kits working with chemical methods are used at the rate of 8%–9% [6,9–11]. Francielli et. al. investigated

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the oxidation compound of olive oil by using the ultraviolet (UV)-visible (VIS) spectrum. Spectrum data were analysed by using independent compound analysis [12]. An amount of Quercetin portion of food was analysed by UV–vis spectrometry enriched with amine-based liquid phase micro-extraction (LPME) [13]. On the other hand portion of the portable spectrometric analysis systems and devices is nearly 1% - 2% level over all food analysis systems [14–16].

Mayr, S. et al. used NIR spectroscopy to analyse Piper nigrum, i.e. black pepper to determine its quality[17]. Besides, researchers analysed different spices including curry, turmeric and paprika to determine food adulteration [18]. They utilised a UV–vis spectrometer to scan the spices for detecting the Sudan I-II-II-IV dyes. In another study, Karık. Ü. et al. utilised UV–vis-NIR spectrometer to determine the quality parameters of the cumin spice acquired from different countries[19]. Cocchi et al. proposed a machine learning algorithm based on NIR spectra data to classify wheat flours in different qualities[20]. De Lima et al. investigated food fraud on black pepper and cumin powder mixed with starch cassava and corn flour using a NIR spectrometer. They classified the acquired spectral data exploiting algorithms such as partial least squares and adulterated samples were distinguished at high accuracy [21]. Park et al. suggest a powerful tool to analyse the content of piperine in black pepper samples by using NIR spectrum analysis assisted with multivariate statistical analysis. In this work, black pepper samples were examined within a NIR spectrometer whose spectrum range varies between 1100 nm to 2500 nm. The extracted features were employed to figure out the considered contents [22]. In another work, the content of wheat in the resistant starch (RS) of green banana flour was studied by using VIS–NIR spectroscopy. The spectrum data for the samples were analysed by adopting the principal component analysis and partial least square regression with a second-order Savitzky-Golay filter. According to the scientific literature, this study carries out important work for the banana industry [23]. Cortes et al. presented a literature survey on the potential applications of VIS–NIR spectrometry for food control, quality and fraud [24]. In the present manuscript, nine different food types were analysed by exploiting hand-held spectrometers. The acquired spectral data were analysed by using several classification algorithms. According to the results, the samples of the same colours were identified successfully, thanks to efficient artificial intelligence algorithms.

According to Market Research, the global portable spectrometer market is expected to reach \$2.77 billion by the end of 2025 from \$1.54 billion in 2019. Low cost, need for fast results, on-site testing and non-destructive operation have created a demand for portable spectrometers including Raman spectrometers, near-infrared (NIR), Fourier Transform Infrared (FTIR) and UV–vis[25]. Portable spectrometers are widely requested in the pharmaceutical, food and agricultural industries and also medical diagnosis[14]. Developments in electronics, i.e. wireless technology, microcontrollers, low-power consumption, fabrication methods and MEMS technology, the physical hardware required in spectroscopy enabled the components to be produced in the form of components: grid, filters, photodiodes, small electronic components, and subsequently allowed the development of compact and low-cost portable optical spectroscopy systems and devices [26]. Lie et al. examined the spectra and quality of some fruit samples by using commercial and portable near-infrared devices[27]. Yang et al. explored sugar contents of fruit samples by using a commercial hand-held VIS/NIR spectrometer (Ocean Optics Inc. US. Model USB4000)[28].

In this study, the design of the device that can perform spectral analysis in the range of 410–940 nm, electronic features, data transfer software, classification algorithms on data belonging to 10 different foods are mentioned. Electronic components AS72651, AS72652 and AS72653 (AMS AG, Austria) with 6-channel photodiode arrays were used for spectral analysis. The spectral sensors (AS72651, AS72652 and AS72653) are standalone components and are mainly employed for colour identification and colour calibration purposes. In this research, we utilize these sensors together with three optical light sources (white, UV and IR LEDs) covering the 410–940 nm range to design and develop a battery-powered, handheld and portable spectrometer combined with a machine learning model for food content analysis. Although some electronic modules integrate one or all of these three sensors [29,30], these modules require external electronic circuitry to power and control the sensor modules, and to transfer the spectral data to the required user interface. Also, the radiant intensity value, the radiant flux per unit solid angle from a point light source emitted in a given direction, of the IR illumination source (VSMY12940, Vishay Semiconductors, US) used in our design has a value of 16mW/sr which is 80 times higher than the one used in the commercial modules (IR19-21C, Everlight Electronics, Taiwan) built around AS72651, AS72652 and AS72653. It indicates much better illumination of the target sample in the IR region[31].

The main purpose of this study is the implementation of a low-cost electronic design and exploiting the machine/deep learning algorithms to improve the performance of the device albeit its poor spectral resolution properties compared to bench-top spectrometer instruments. Moreover, the present study focuses on the necessary software for transferring the data to the computer environment employing a user-friendly interface. By exploiting state-of-art classification techniques, we manage to tackle the disadvantage inherited from the low spectral resolution of the electronic design. Therefore, our approach achieves high classification accuracy of up to 97% for detecting the foods.

2. Materials and method

2.1. Food samples

Spectrometric measurements were carried out in nine different food items such as red pepper, black pepper, cumin, cinnamon and curry, -easily distinguishable by the human eye hence their colours- and generally in white colours and shades of flour, gluten-free flour, starch and powdered sugar were carried out. On the other hand, flour and gluten-free samples are not only of the same colour but are also similar to each other in terms of their grain properties. In the same way, powdered sugar and starch are close to each other. Food samples were provided as products sold by different brands in the markets. 150 different measurements were performed for each food sample. During the spectrometric measurements, the atmospheric conditions of the laboratory were kept constant ($23^{\circ}C \pm 1, 50\%RH$). After each measurement process, the sample holder of the device was cleaned with distilled water as well as alcohol and then dried. Thus, the effect of any contamination on the food sample of any liquid residue is prevented. All measured data by the developed device was presented in the *GitHub* repository Schematic Sensors 2021-08-16.pdf.

2.2. System design and development

To carry out spectrophotometric measurements of food items between 410 nm and 940 nm, a portable optoelectronic device was designed and produced. The optoelectronic device consists of two separate parts; a control board and a sensor board, which can be connected through easy-to-plug cables. The sensor board include light sources for the illumination of food items and sensors to identify reflected light from the food. AS72651, AS72652 and AS72653 (ams AG, Austria) sensors were used for spectral identification of light from the VIS to NIR range. Each sensor has six integrated on-device Gaussian Band Pass filters with 20 nm Full Width at Half Maximum (FWHM) value and with three sensors, we achieved spectral response between 410 nm and 940 nm with 20 nm FWHM. The sensors also have integrated programmable constant current led drivers, eliminating external led driver design and minimizing the PCB space. During the operation, AS72651 acts as master, while the other two sensors act in slave mode. The microcontroller sends the commands to AS72651 via I2C and receives all readings from sensors through AS72651. The electronic circuit design belonging to each spectral component was presented in *GitHub* repository measured data file as Data.xlsx. The sensor board also includes flash memory with firmware to flash the sensors. AT25SF041 was used as flash memory for the sensor module and firmware from AMS AG company was loaded into it. To illuminate food samples and fully cover the 410 – 940 nm range, 3 light sources, UV, White LED and IR LED, were exploited as light engine modules. VLMU3100 (Vishay Semiconductors, US)[32], Luxeon 3014 (LUMILEDS, US)[33] and VSMY 12940 (Vishay Semiconductors, US)[34] were included in the design as UV, white and IR leds respectively. The control board consists of a power stage, a microcontroller unit (MCU), a communication unit, a USB for communication and a battery charging circuit. The power stage includes reverse polarity protection and DC-DC buck converter circuits. The DC-DC buck converter circuit was provided in *GitHub* as model images/power circuit.

The device is powered through 1S $3.7V$ $280mAh$ rechargeable Lithium polymer battery. As low battery voltage, using a diode as reverse polarity protection will result in a further drop in the voltage by $0.3 - 0.7V$ based on the preferred diode type. We have used Si2301CDS (Vishay Semiconductors, US) as a p-channel Mosfet for reverse polarity protection circuit to achieve almost zero voltage drop. To convert battery voltage to $3.3V$ to power MCU, sensors, communication units, synchronous buck converter was designed using TPS62063 (Texas Instruments, US). The IC contains a fixed 3 MHz switching frequency which allows optimum operation with small inductor sizes [35]. By following the design procedure given in [35], the inductor value was chosen to be $1\mu H$, while $10\mu F$ ceramic capacitor was used as an output filter. Atmega328P-AU was used as MCU on the board. The MCU involves 8 on-board analog pins, 13 I/O pins which can be used as both input and output. The MCU operates at 16 MHz crystal frequency [36]. Taking into account low power consumption requirement of the device, we have included Bluetooth Low Energy 4.0 as data transfer unit on the design. The module is designed around CC2541 BLE chip (Texas Instruments, US) and consumes $270\mu A$ in low power mode [37]. We also included USB interface to transfer data to the user interface during test stage. FT232RL (Future Technology Devices International Ltd., US) chip was used for the USB – UART interface. When the device was powered through lithium polymer battery, attention must be paid during charging the lithium polymer batteries as overcharging them may result in unstable conditions, thermal runaway and the batteries may go up in smoke [38]. The batteries require a constant current voltage charging mechanism to fully charge the battery and also, the power must be cut off when charging finishes [38] Taking into account these parameters, we have designed a constant current constant voltage battery charging system for lithium polymer battery around MCP73831 chip (Microchip Technology, US) The IC has constant current constant voltage charging algorithm, small package and is suitable for space limited applications [39]. Open source Easyeda software was used for PCB design. Control board was designed onto 2-layer PCB. Bottom layer was used to be solid ground plane and all routing were made on top layer. We removed copper under the inductor of DC-DC buck converter to minimise the noise of the switching. Sensor board was on 4-layer PCB. Attention was pain in order not to pass any digital lines under the sensor IC so that the readings are not affected. Also, USB – UART interface was included in the design via FT232TL (Future Technology Devices International Ltd., US) 3D image of control and sensor boards were given in *GitHub* repository model images (see Fig. 1).

The parametric design of the plastic enclosure (called outer sheath), sample holder and light coverage was carried out through the platform called Onshape (Onshape Inc. Boston, MA), which allows CAD design in open access and web environment. After the parametric design of the outer sheath was converted to **.STL* format, it was produced with a 3D printer. The control board and sensor boards were placed into the 3D printed plastic enclosure. The parametric design files were presented in the *GitHub* repository 3D models as parametric design files. The fabricated spectrophotometric devices include control and sensor boards with plastic enclosure and sample holder were presented in Fig. 2.

2.3. Data acquisition and classification phase

2.3.1. Data acquisition

A user-friendly GUI (graphical user interface)-based application was developed to perform measurements with a portable spectrometer device and to determine the food type. The application flow and the corresponding GUI page are displayed in the top side of Fig. 2. In general, the properties of GUI are listed as below;

- Main control over the fabricated devices
- Collection of the spectrophotometric data
- Storing acquired data
- Visualization of the measured spectrometric data
- Classification of food samples by employing a pre-trained machine learning model

With the developed interface, the data received over the serial port connection of the spectrometer device is stored in a *.txt* file specified by the user. With the completion of the spectrophotometric measurement, the acquired data is exploited as the input for the pre-trained SVM and CNN models. Subsequently, the classification phase starts and the results returned.

2.3.2. Classification Phase

Initially, the data acquired from the sensors were collected and labelled accordingly.

Before the classification phase, the number of features was reduced to 3 dimensions using the Principal Component Analysis (PCA) [40]. Thus, we visualized the distribution of the labelled data as an exploratory analysis approach. The corresponding demonstration employing the first three principal components is presented in Fig. 4.

The labeled data was initially normalized and then classified by the machine learning and deep learning approaches. SVM and CNN methods were performed for the classification of foods according to their types. In each method, the corresponding data was split into two parts, that is, train and test. These portions were randomly selected and experiments were run several times for the stability of the results. The average values of the performance metrics calculated for each experiment are presented.

The user interface application for CNN was developed in Visual Studio using C#.NET. Keras.NET was adopted for food type classification. Keras.NET is a high-level deep neural networks API for C# via a Python binding and exploits the TensorFlow backend. The constructed 1D CNN model exploits 18×1 vectors as input elements. In this model, by performing a 1D convolution process by exploiting a 1D kernel of size 3×1, 64 feature maps were created.

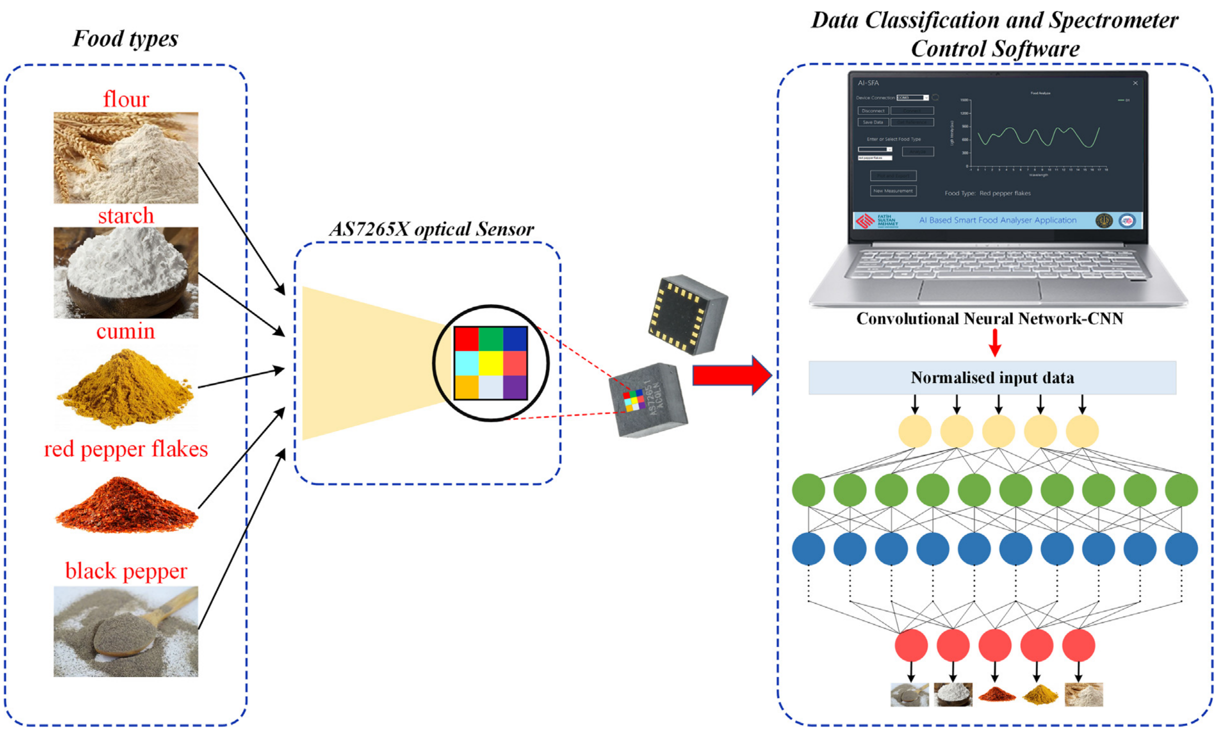

Fig. 1. Block diagram of a portable Spectrometer.

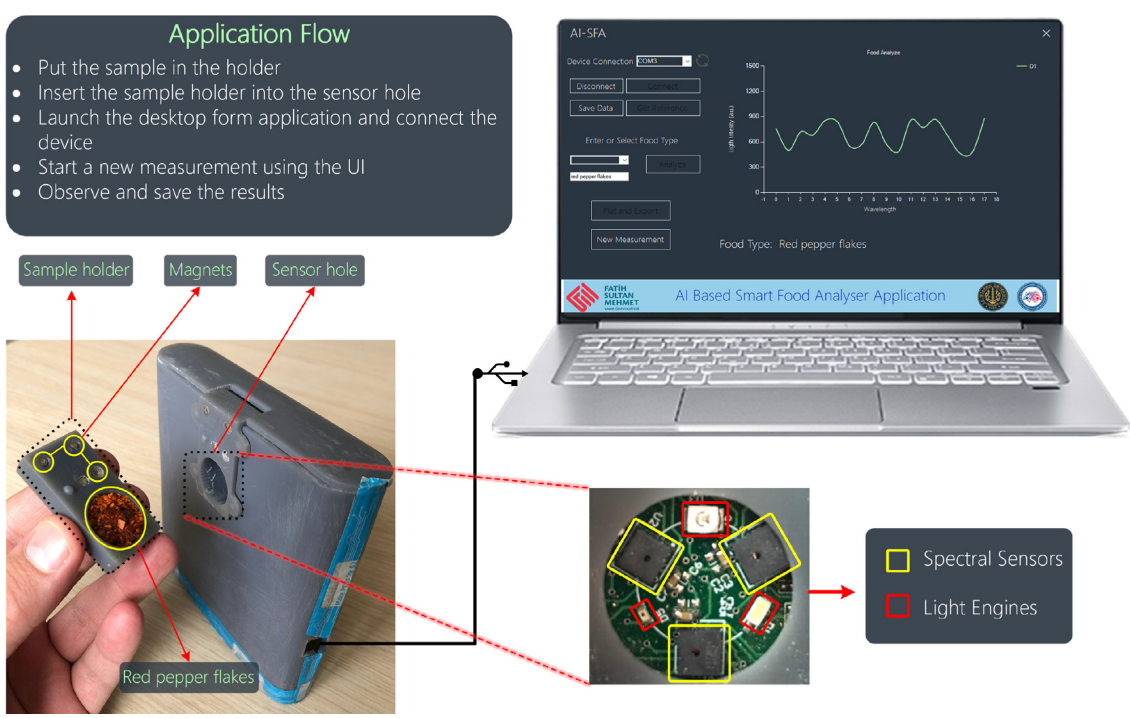

Fig. 2. Schematic illustration of working principle diagram of spectrometer device.

Maps having 32 features were obtained by applying 2 convolution operations consecutively with a filter size of 3×1.

Then, the input vector is halved with a 2×1 max-pooling filter. Afterwards, the other 2 convolutions were applied to 32 and 64 feature maps, respectively, in which the feature extraction process was completed. For the classification stage, we employed two fully connected layers consisting of 64 and 128 neurons, respectively and an output layer consisting of 9 neurons. In the constructed CNN model, the epoch count was fixed at 100. The corresponding loss function was selected as Adam's loss function [41] whereas the activation function was picked as ReLU. In the output layer, the activation function was adopted as softmax where the categor-

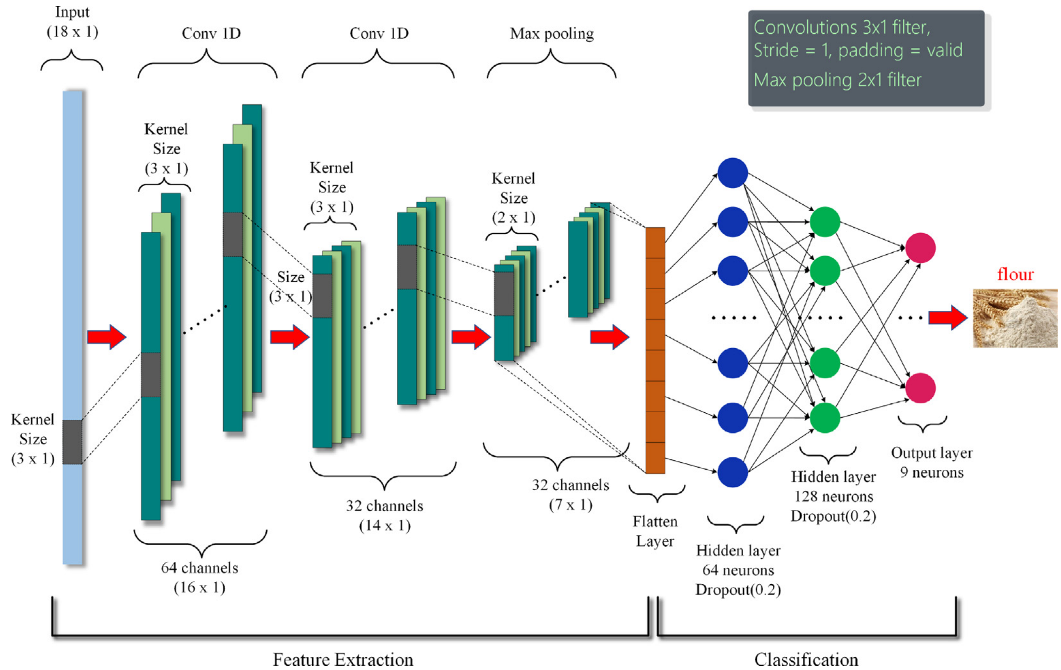

Fig. 3. 1-D convolutional neural network (CNN) structure created for food types classification.

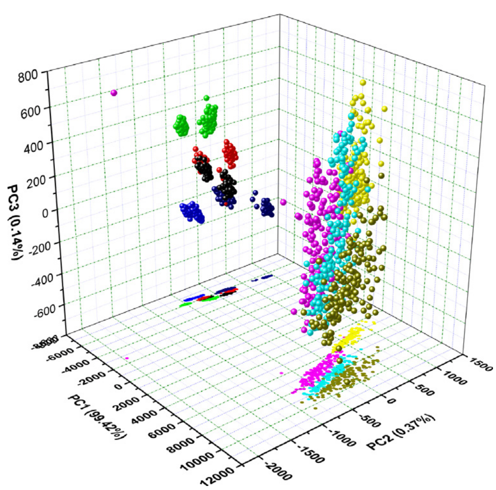

Fig. 4. Data projected on the first three principal components.

ical cross-entropy was exploited as the output loss function. Schematic illustration of Deep Neural Network structure is presented in Fig. 3.

The received data by the fabricated spectrometer are normalized with L_2 normalization before being given as input to the CNN network and each input is labelled with one-hot-encoding.

3. Results and discussion

3.1. Device characteristics

To verify the important parts of the circuit before the PCB design, we performed simulations and examined the results to see if they comply with design requirements. For this purpose, the power stage of the control board was simulated using WEBBENCH Power Designer (Texas Instruments, US). The load current was adjusted to 600 mA and the maximum input voltage was chosen to be 4.2 V. The steady-state response of the power stage for the designed electronic circuit at 600 mA load current was presented in the ESI (Electronic Supplementary Information-GitHub repositoryhttps://github.com/msaaydin/AI-SFA). According to that figure, there is no voltage drop in the output at 600 mA load current which is around 3 times higher than the maximum peak current that the device can draw during led illumination.

3.2. VIS–NIR spectra

The tested powdered food samples were obtained from products sold by different brands in the markets. The sampling capsule was cleaned before reflectance spectrum measurements by acetone, alcohol and distilled water and then were dried in the air ambient. Gluten-free flour and flour cannot be distinguished from each other in terms of colour, odour and texture. The Reflectance spectrum of gluten-free flour (top) and flour (bottom) were given in Fig. 5(a). Light intensity value versus relevant wavelength was calculated by the mean value of all measured data versus wavelength. The standard deviation was plotted as blue coloured and observed that the deviation value is decreasing by increasing the wavelength. On the other hand, the deviation is very low compared to the relevant light intensity value of the relevant wavelength. Moreover, the reflectance spectrum of the tested different types of food samples was given in Fig. 5(b). In this study, foods were determined into two groups, coloured and non-coloured (as white). By using the spectral slope, coloured and non-coloured foods are quickly separated from each other (Fig. 5b). However, when we evaluate the spectral curves of each food group among themselves, it is observed that the results are close to each other and the separation between food types becomes difficult. In both graphs, light intensity values were almost the same. This fact occurs due to the low power of IR LED. Although the reflectance spectra and the light intensity values corresponding to each wavelength are close to each other, classification experiments in this work were successfully maintained by the developed device (see Fig. Fig. 6).

Spectral region of the final device was comparable to the ones reported in other studies where benchtop and handheld instru-

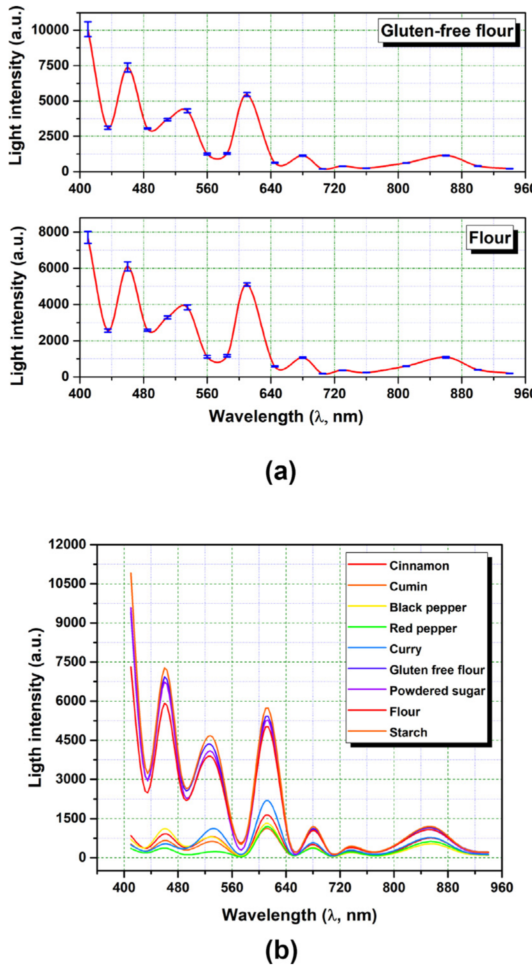

Fig. 5. (a) Reflectance spectrum of (a) gluten free flour (top) and flour (bottom) and (b) all tested different types of foods.

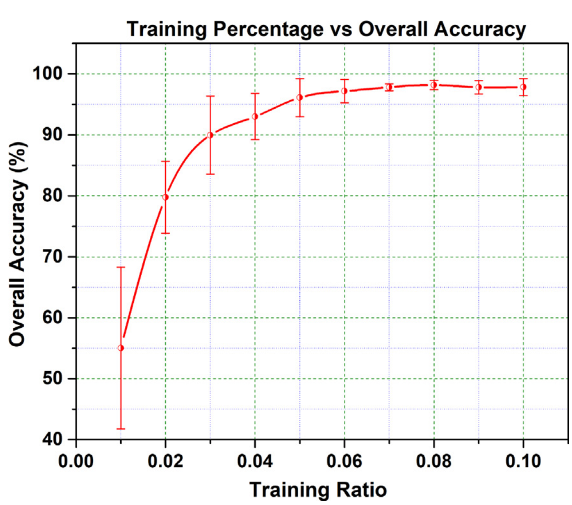

Fig. 6. Classification results obtained using SVM for various training percentages.

ments were used. Mayr S. et. al. used near-infrared spectroscopy for quality control of black pepper and compared the performance of different benchtop (735–2632 nm) and portable spectrometers (740–1069 nm)[17]. Lim J. et. al. tested red pepper powder in the visible and near-infrared spectral region (350 – 950 nm) to determine the capsaicinoids content[42]. Cinnamon, cumin and curry are another spices whose spectral scanning was made using UV VIS NIR spectrometers in [43,19,44] to determine the adulteration and quality parameters. Starch spectral analysis was examined in 400 – 2400 nm range using Foss NIRSystems Model 6500 (Foss Analytical, Denmark)[45]. Zandomeneghi M. et. al. used spectrometer to scan the flour in 250–650 nm range to determine the carotenoids[46]. Lopez M.G. et. al., scanned carbohydrates including powdered sugar in near-infrared region and used statistical and mathematical methods to characterise carbohydrates[47].

3.3. Classification and Overall Accuracy Results

In this work, two fundamental classification approaches were followed. The first one of these methods is a flexible and efficient machine learning algorithm called *Support Vector Machines (SVM)* [48]. SVM is a supervised machine learning algorithm for classifying high dimensional data (i.e. vectors). SVM aims to construct a hyperplane which leaves the margins with the nearest cluster point widest possible. Although, SVM was proposed for binary classification problems, it may be extended to multi-class classification tasks without any difficulty. SVM is also capable of distingu ishing linearly non-separable data. This attribute of SVM can be employed by performing the “kernel trick” by implementing a certain non-linear kernel function instead of the linear one [49]. After determining the kernel type, the data under consideration is split into training and testing samples, respectively. First, the algorithm is fed using the training data, say D_{train}. With the help of the samples in D_{train}, the SVM algor ithm generates the decision boundaries which isolate each data group having the same label. Thus, the learning model is constructed. Then, the testing samples, that is D_{test} are infused into the trained SVM model. Finally, the model determines the labels of each data sample in D_{test} using the model established in the training phase. The fundamental classification performance metric, overall accuracy (OA), for the given data set is calculated as

$$\mathbf{OA} = \frac{\text{Numberofcorrectpredictions}}{\text{Numberoftestingdatasamples}} \tag{1}$$

However, though OA is an important efficiency metric for classifier evaluation, it could present limited information about the stability and sensitivity of the proposed classifier. To this end, the sensitivity, specificity, precision, Matthew’s Correlation Coefficient (MCC) and Cohen’s Kappa metrics were also reported. In SVM experiments, we employed the radial basis function as the non-linear kernel function. To determine the optimal kernel parameters, c and γ, we performed 5-fold cross-valida tion and grid search after applying min–max normalization. We exploited the LIBSVM tool [50] to implement the SVM classification algorithm. Each experiment was carried out with 20 independent trials on randomly selected training samples. Then, the above-mentioned machine learning metrics were calculated benefiting the constructed confusion matrix for each run. The reported values are the average of 20 trials.

The latter classification approach in this work is Convolutional Neural Networks (CNNs). As a result of the test with the trained network, an accuracy of 95.87% was obtained. This accuracy value is the average of large values of 10 runs over and over. Each time, all the data, 80% as training and 20% as test data, were reused, thus revealing the performance of the network in a random way. The CNN network has been trained for 500 epochs. During the training, 10% of the input data was used as validation data. Fig. 7 a,b showed a large number of epochs in the validation and training accuracy of the CNN network and training that the best accuracy was achieved.

In Table 1, it is obvious that all metrics except Cohen’s κ were computed higher than 0.80. These values indicate that the SVM

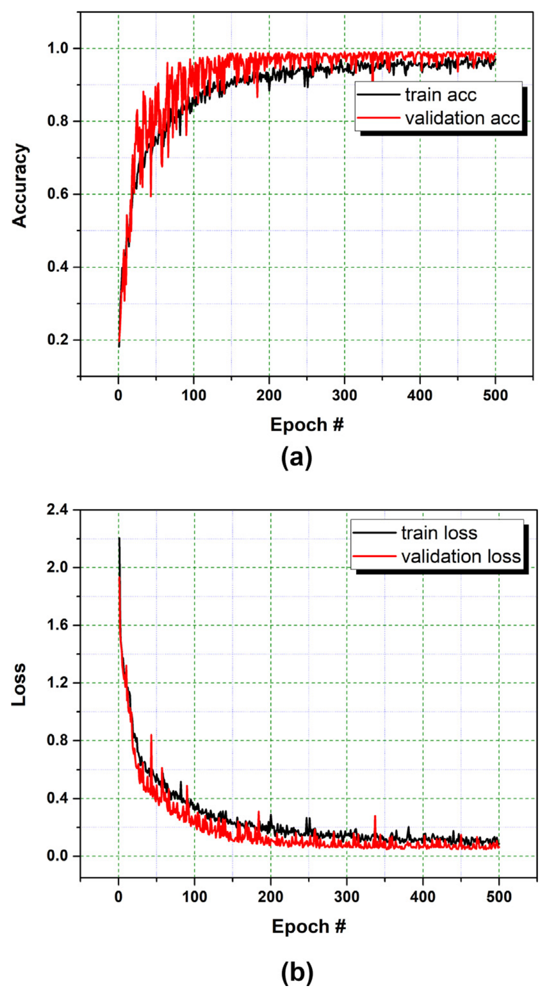

Fig. 7. CNN network training and validation accuracy results (a), CNN network training and validation loss results (b).

classifier produces stable and reliable performance in classifying the considered data. On the other hand, the κ value for 2% and 4% training ratios were considered inadequate. These observations imply that the classification results at 2% and 4% training ratios could not satisfy the competent accuracy performance in sense of reliability. Furthermore, for 6% and higher training percentages, the κ values are higher than 0.82 which could be acknowledged as the SVM method yields reliable results for the considered training ratios.

After assessing the SVM classifier performance, we evaluated the same machine learning metrics for the proposed CNN based classification method and reported in Table 2. According to the results in 2, the CNN based classification results are close to 1.0 which indicates that the performance of the classifier is reliable and valid for the data under consideration. The results interprets that the CNN metrics are similar to the metrics acquired by the SVM which assesses 6% as the training percentage.

Table 2
CNN Classifier performance metrics ratio.

Sensitivity	0.967
Specificity	0.996
Precision	0.971
MCC	0.966
Cohen's κ	0.855

All developed codes and data is accessible in the corresponding *GitHub* repository link.

4. Conclusions

By adopting the do-it-yourself philosophy as the basic principle, the portable and hand-held photospectrometer device, software and classification algorithm processes were created and tested on real food samples. It is aimed to disseminate science and technology while supporting researchers who aim to develop an integrated structure by dealing with electronic device design, developed device, computer and user interactions and coordination, data classification and all parameters, especially those who carry out their studies at undergraduate and graduate levels. The devised electronic structure, tests, user interfaces (GUI), data classification algorithms and design criteria proposed in the present manuscript are shared with on *GitHub*.

The electronic structure of the spectral part of the developed device has employed three different spectral sensors (AS72651, AS72652, AS72653) each of which has six photodiode arrays equipped with 20 nm FHWM optic band-pass filters and LEDs capable of radiating in the UV–vis-IR band range. The developed portable and handheld spectrometer can receive data from 18 different points between 410 nm and 940 nm, and its optical resolution has been improved to approximately 30 nm. To show the optical analysis power of the device, reflectance analyses were performed against 9 powdered different food types. It has been observed that the reflectance values of foods, which are seen as white when viewed with the naked eye, are close to each other and classification has not been possible. SVM and CNN algorithms have been developed for the analysis of reflectance data and subsequent determination of measured 9 different types of foods. The classification accuracies of SVM and CNN algorithms are 97% and 95%, respectively. The reported metrics indicate that the classification performances of both methods are adequate, valid and reliable.

Author Contributions

S.O. conceived the project, wrote the manuscript, acquired the data and prepared the figures; S.H. and C.F. built the prototype; M.A. designed and developed GUI, implemented the CNN algorithm, assisted in writing the manuscript and prepared some of the renderings; S.T. performed the classification algorithms, evaluated classification results and assisted in writing the manuscript.

Table 1
SVM Classifier performance metrics for varying training ratio.

	2%	4%	6%	8%	10%
Sensitivity	0.832	0.937	0.966	0.982	0.984
Specificity	0.979	0.992	0.996	0.998	0.998
Precision	0.887	0.948	0.967	0.982	0.984
MCC	0.825	0.932	0.962	0.980	0.982
Cohen's κ	0.317	0.675	0.825	0.906	0.919

All authors reviewed and approved the final version of the manuscript.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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