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FruVegy: An Android App for the Automatic Identification of Fruits and Vegetables using Computer Vision and Machine Learning

Anish Appadoo[1], Yashna Gopaul[1] and Sameerchand Pudaruth[1]

[1]*Department of Information and Communication Technologies, University of Mauritius, Reduit, Mauritius*

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Abstract: Nowadays, many people are unaware of the benefits of fruits and vegetables which has resulted in their reduced consumption. This has inevitably led to a rise in diseases such as obesity, high blood pressure and heart diseases. To this end, we have developed FruVegy which is an android app which can automatically identify fruits and vegetables and then display its nutritional values. The app can identify forty different fruits/vegetables. The app is specially targeting school students who will find it easy and fun to use and this, we believe, will increase their interest in the consumption of fruits and vegetables. Furthermore, the names of the fruits and vegetables are also available in French and in Mauritian Creole. Our dataset consists of 1600 images from 40 different fruits and vegetables. There was an equal number of images for each fruit/vegetable. To our knowledge, this is the largest dataset that currently exists in literature. Features such as shape, colour and texture were extracted from each image. Different machine learning classifiers were tested but random forest with 100 trees produced the best result with an accuracy of 90.6%. However, with TensorFlow, an average accuracy of 98.1% was obtained under different scenarios. In the future, we intend we increase our dataset and the number of features in order to achieve an even higher accuracy.

Keywords: fruits; vegetables; identification; mobile app; machine learning; computer vision.

1. Introduction

Fruits and vegetables act as a protector against several diseases and prevent the onset of medical conditions such as diabetes, high blood pressure and heart diseases. Because of our hectic lives, many people often tend to neglect their health, by ignoring what they consume, even though a proper diet can simply be supplemented by fruits and vegetables [1]. According to the World Health Organization (WHO, unhealthy diets are one of the leading causes of non-communicable diseases [2].

Furthermore, we have noticed that there is an absence of m-Health tools in Mauritius. Thus, the development of a fruits and vegetables recognition application will be beneficial for the public in general. To target the maximum number of users, the app will be developed for the Android platform. On a global scale, more than 80% of smartphone users have a Samsung device and this is also the trend in Mauritius. It is also trite law in Mauritius that the majority of students in secondary schools have a smartphone and most students in primary schools know how to use a smartphone or tablet. They know how to access the internet, watch videos from YouTube, listen to their favourite songs and music and how to download and install games and other apps from Google Play.

Thus, the main aim of this work is to develop an Android-based fruits and vegetables identification system which will allow a user to capture a picture and then launch the automatic identification system which is based on artificial intelligence techniques. Once the produce is identified, its name will be displayed in the most commonly used languages in Mauritius which are English, French and Mauritius Creole. The properties and the health benefits will also be displayed. The application is intended to be very simple to use. Moreover, FruVegy will not require an internet connection to function. The application also does not require high resolution images to provide high accuracy. Any Android phone equipped with a camera can be used.

This work has made several contributions. Firstly, our system makes use of 40 categories of fruits and vegetables which is the largest number of categories that have been used so far. Secondly, our system has the highest accuracy

E-mail address: anish.appadoo@umail.uom.ac.mu, yashna.gopaul1@umail.uom.ac.mu, s.pudaruth@uom.ac.mu

compared with all existing systems. Thirdly, there were no manual pre-processing steps in the training stages. This partly explain the high accuracy achieved in the testing phase as we should not expect users to know how to take model-friendly images. Fourthly, and very importantly, while many existing systems works only on a desktop computer, our artificial intelligence model has been integrated into a mobile application, which can easily be deployed and use by anyone having an Android smartphone.

This paper proceeds as follows. In the next section, several related works are identified and summarised. The methods are described in section 3 while the results are described and evaluated in section 4. Section 5 concludes the paper with a brief note on future works.

2. Related Works

The recognition of fruits and vegetables is an important problem in industry where selection and categorisation of fruits and vegetables into different grades and sizes must be made. Thus, a lot of work has already been done in this field in the past decade. Some of these works are reviewed in this section.

Rocha et al. (2008) used Unser's descriptors to classify 11 types of fruits from the supermarket produce dataset which they created. 2078 images were used which resulted in an accuracy of 96.6% [3]. In 2010, they used 2633 images and obtained an accuracy of 95% using support vector machines [4]. Seng and Mirisaee (2009) proposed a method that used three features, namely, colour, shape, and size [5]. The k-nearest neighbour (KNN) algorithm was used to perform classification through the Euclidean distance measure. The features used were mean colour, shape roundness, area and perimeter. An accuracy rate of 90% was achieved with 7 categories of fruits.

Selvaraj et al. (2010) performed fruit recognition using the colour and texture features [6]. HSV (Hue Saturation Value) representation was used for feature extraction because of its invariant characteristics. An accuracy of 86% was achieved on the supermarket produce dataset with 15 different types of fruits. An accuracy rate of 89.4% was achieved using the Multilayer Perceptron algorithm on the supermarket produce dataset by Chaw and Mokji (2012) [7]. Colour features such as the mean of the red, green, blue, hue, saturation and value channels and texture features based on the grey level co-occurrence matrix (GLCM) such as contrast, correlation, energy, and homogeneity were extracted from the region of interest (ROI).

Dubey and Jalal (2012) opted for the Improved Sum and Difference Histogram (ISADH) texture feature using the supermarket produce dataset with 2615 images and 15 different types of fruits [8]. This resulted in a near prefect accuracy of 99%. In a more recent study, Dubey and Jalal (2015) used the k-means clustering technique for segmentation [9]. A global colour histogram, a colour coherence vector and a colour difference histogram were used as colour features while the structure element histogram, local binary patterns, local ternary pattern and completed local binary pattern were used as texture features. A combination of the global colour histogram and local binary patterns produced the highest accuracy of 93.8%. All the experiments were performed on 2612 images from the supermarket produce dataset with 15 different types of fruits being used.

Kim et al. (2014a) developed a mobile application for the identification of fruits based on colour, shape and texture features [10]. Experiments were carried out on 1006 fruit images and 33 different fruit categories. An accuracy of 94.7% was achieved. A few months later, Kim et al. (2014b) improved their previous system by using a genetic algorithm (GA) to select the best features and this resulted in an improvement of 3% over their previous system [11]. Zawbaa et al. (2014) applied random forest (RF) algorithm to classify three different categories of fruits [12]. The scale invariant feature transform (SIFT) algorithm, colour variance, mean colours, colour kurtosis, colour skewness, eccentricity, centroid, and the Euler number were used as features. The accuracy of this approach was well below existing systems.

Zhang et al. (2014) introduced a classification method involving a combination of fitness-scaled chaotic artificial bee colony (FSCABC) algorithm and a feedforward neural network (FNN) [13]. A fruit dataset of 1653 images, split into 1322 images for the training set and 331 images for the test set, comprising 18 categories, was used in this system. An accuracy rate of 89.1% was achieved.

Huawei et al. (2014) used colour completed local binary patterns (CCLBP) for texture feature extraction. After experimenting with several algorithms, the CCLBP, HSV colour histogram and BIC colour histogram combination was found to achieve the best accuracy [14]. Images were converted from RGB colour space to Lab colour space and classified using the K-means clustering method. 180 images from 13 categories of fruits were used: 30 for training and 150 for testing. An accuracy rate of 75.8% was achieved.

Sakai et al. (2016) proposed a deep neural network (DNN) which extracts the relevant features directly from the image pixels [15]. 200 images from 8 different categories of vegetables were used: 160 for training and 40 for testing. An accuracy rate of 97.6% was achieved. Hou et al. (2016) performed a similar work on a dataset consisting of 5330 images from 7 categories of fruits out of which 4000 images were used for training and 1330 images were used for testing [16]. A near perfect accuracy of 99.8% was achieved.

Wang et al. (2016) developed a fruits and vegetables recognition system based on mature feature extraction algorithms [17]. The features considered were contour, colour, and texture. A total of 1358 images were used in the dataset out of 908 were placed in the training set and 450 in the testing set. Eleven categories of produce were used in this study. An accuracy rate of 97.4% was achieved.

Zhang et al. (2016) had proposed a new system for the classification of fruits on the optimization of biogeography and feedforward neural network which they named as BBO-FNN [18]. Using 18 different categories of fruits, they were able to achieve an accuracy of 89.1%. Their novel technique performed better than many other nature-inspired algorithms. The algorithm was also efficient in terms of time.

Cornejo and Pedrini (2017) proposed the fusion of the census transform histogram (CENTRIST) with the hue-saturation (HS) histogram [19]. Classification was carried out using KNN and support vector machines (SVM) so that their recognition rates could be compared. An accuracy of 97.3 was achieved on 15 categorise of fruits from the supermarket produce dataset.

Xue et al. (2020) achieved an accuracy of 95.9% using an attention-based densely connected convolutional network with a convolution autoencoder (CAE-ADN) on the Fruit 26 dataset [20]. Their proposed model performed slightly better than the ResNet-50 and DenseNet-169 models.

Using the Fruit 360 dataset, Ukwuoma et al. (2022) achieved an accuracy of 95% using a deep learning model which they implemented from scratch [21]. They also achieved an accuracy of 99% using the ResNet-50 architecture on the same dataset. Ibrahim et al. (2022) obtained an accuracy of 99.8% on a dataset consisting of 14 different fruit images [22]. Their proposed CNN model outperformed ResNet-20 and SVM. A summary of all these studies is provided in Table I.

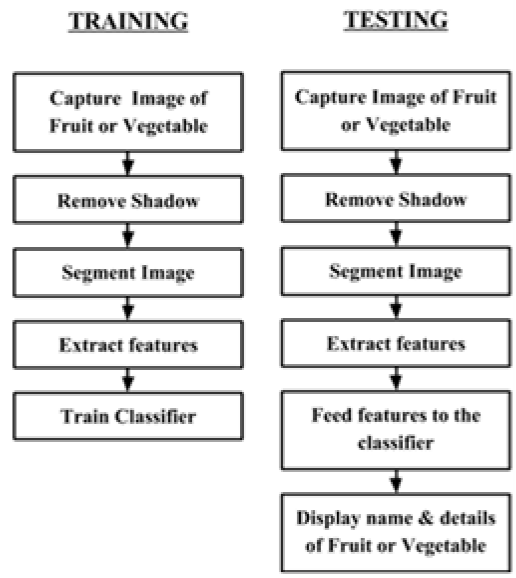

Figure 1. Classification and Identification Algorithms

Figure 2. Original Image of a Dry Coconut

3. Methodology

Our proposed approach is divided into two phases: training and testing. Both phases include the same steps up to the extraction of features. Training involves the generation of a classification model while testing involves feeding the extracted features to the model to identify the fruit/vegetable.

A. Dataset

We populated our dataset with images of fruits and vegetables which are commonly available in Mauritius. This is also a major contribution of this study. There is a total of 1600 images on 40 different fruits/vegetables and 40 different images were taken for each fruit/vegetable. The fruits and vegetables were placed on a white background and their images were captured using different smartphones. The full list of fruits and vegetables used in this study is provided in the confusion matrix in Appendix 1.

B. Pre-processing

After loading the image (Fig. 2), it is converted from the RGB colour space to the HSV colour space as the segmentation of the fruit/vegetable is usually better in this colour model. Different colour spaces such as RGB, HSV, YUV and YCrCb were tested but HSV was selected as its 'H' and 'S' component were able to differentiate between the fruit/vegetable and its shadow. An adaptive thresholding algorithm is applied either on the hue (H) or saturation (S) component, depending on the average blue intensity of the image. The image is eroded and dilated twice successively to remove noise. The base features like width, height, perimeter, and area are then extracted from the black and white image (Fig. 3). Adaptive thresholding has the ability to remove the shadow from the original image. The black and white mask (Fig. 3) is then overlaid onto the original image. The black pixels are made opaque while the white pixels are made transparent. The contour of the fruit/vegetable is obtained by using the 'findCountour' function from the OpenCV library, as shown in Fig. 4.

TABLE I. Summary of related works

Paper	Features	Classifiers	Categories	Training	Testing	Accuracy%
Rocha et al. (2008)	Colour, Texture	BLDA	11	1056	1022	96.6
Rocha et al. (2010)	Colour, Texture	SVM	15	600	2033	95
Seng and Mirisaee (2009)	Colour, Shape, Size	KNN	7	36	14	90
Selvaraj et al. (2010)	Colour, Texture	MDC	15	1314	1326	86
Dubey and Jalal (2012)	Texture	SVM	15	600	2015	99
Dubey and Jalal (2015)	Colour, Texture	SVM	15	900	1712	93.8
Kim et al. (2014)	Colour, Texture, Shape	KNN	33	920	86	94.7
Kim et al. (2014)	Colour, Texture, Shape	ES	36	980	128	98
Zawbaa et al. (2014)	Colour, Shape	RF	3	125	53	85.6
Zhang et al. (2014)	Colour, Texture, Shape	FSCABC	18	1322	331	89.1
Huawei et al. (2014)	Colour, Texture	KNN	13	30	150	75.8
Sakai et al. (2016)	Dynamic Feature Extraction	CNN	8	160	40	97.6
Hou et al. (2016)	Dynamic Feature Extraction	CNN	7	4000	1330	99.8
Wang et al. (2016)	Colour, Texture, Contour	SVM	11	908	450	97.4
Zhang et al. (2016)	Colour, Shape, Texture	FNN	18	1322	331	89.1
Cornejo & Pedrini (2017)	Colour, Texture	SVM, KNN	15	2106	527	97.2
Xue et al. (2020)	Dynamic Feature Extraction	CNN	26	85260	38952	95.9
Ukwuoma et al. (2022)	Dynamic Feature Extraction	CNN	120	60498	20622	95
Ukwuoma et al. (2022)	Dynamic Feature Extraction	ResNet-50	120	60498	20622	99
Ibrahim et al. (2022)	Dynamic Feature Extraction	CNN	14	2660	1140	99.8

TABLE II. Derived Features

boxArea	boxWidth * boxHeight
boxPerimeter	2 * (boxWidth + boxHeight)
Aspect Ratio	boxWidth / boxHeight
Area Ratio	boxArea / Contour Area
Perimeter Ratio	boxPerimeter / Contour Perimeter
Circularity	(4 * π * Contour Area) / (Contour Perimeter)^2
R:G	Mean Red / Mean Green
R:B	Mean Red / Mean Blue
G:B	Mean Green / Mean Blue
Red%	(Mean Red * 100) / (Mean Red + Mean Blue + Mean Green)
Green%	(Mean Green * 100) / (Mean Red + Mean Blue + Mean Green)
Blue%	(Mean Blue * 100) / (Mean Red + Mean Blue + Mean Green)
Mean Grey	greyIntensitySum / pixelCount
Variance	σ(No. of pixelsz – Mean Grey)^2 P(No. of pixelsz), for z = 0 to 255
Standard Deviation	Variance$^{0.5}$
Skew	(Mean Grey - Mode) / Standard Deviation
Energy	σ(P(No. of pixelsz))^2, for z = 0 to 255
Entropy	-σP(No. of pixelsz) log_2 (P(No. of pixelsz)), for z = 0 to 255

C. Feature Extraction

The formulae for the colour, texture and shape descriptors are illustrated in Table II. Eighteen features were computed from more basic features like the width and height of the image and the red, green, blue, and grey values of the pixels.

4. Results and Evaluation

Different classifiers have been tested using a 10-fold cross validation technique in the RapidMiner Studio [23]. This means that 90% of the dataset is used for training and the remaining 10% is used for testing. Furthermore, this process is repeated 10 times with a different testing set such that in the end, each and every image in the dataset has had the opportunity to appear in one of the testing sets. The performance metrics from each of these 10 folds are averaged to get the final scores. All the machine learning algorithms were used with their default parameters. Table III shows that a random forest with 100 trees produced the highest accuracy of 90.6%. The confusion matrix is provided in Appendix A.

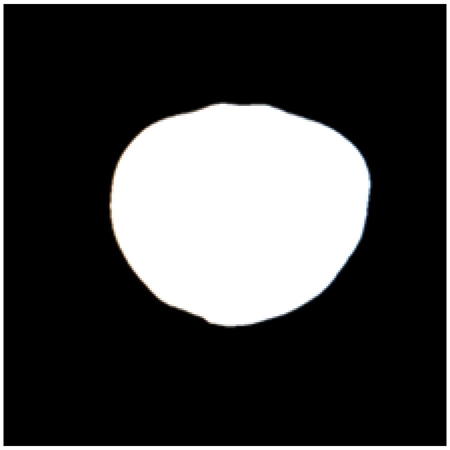

Figure 3. Segmentation of Dry Coconut

Figure 4. Contour Image of a Dry Coconut

Further experiments were carried out to understand the effect of varying the number of images in a category on the accuracy. Figure 5 shows that for every 10 additional images (per category) that is added to the dataset, there is a small increase in the accuracy.

Another investigation was carried out to observe the effect of varying the number of categories on the accuracy. As the number of categories increases, there is a noticeable decrease in the accuracy, as shown in Figure 6.

With only 10 categories of fruits/vegetables, a very high identification accuracy of 98.3% was obtained. After doubling the number of categories, the accuracy fell to 96.1%, a reduction of 2.2%. After a further doubling, the accuracy fell to 90.6%, a reduction of 5.5%. Our accuracies are comparable to those obtained in literature. We should point out that our dataset is the largest that has been used so far in this field. Increasing the number of images per category increases the accuracy, though by a small amount. Hence, in the future, we intend to create a larger dataset with more images per category and possible with additional classes of fruits and vegetables.

TABLE III. Performance of Classifiers

Classifier	Accuracy (%)
Random Forest (100 Trees)	90.6
Neural Network	84.8
Naïve Bayes	83.8
Decision Tree (Information Gain)	78.1
KNN (k = 1)	52.4

Figure 5. Effect of varying number of images per category on accuracy

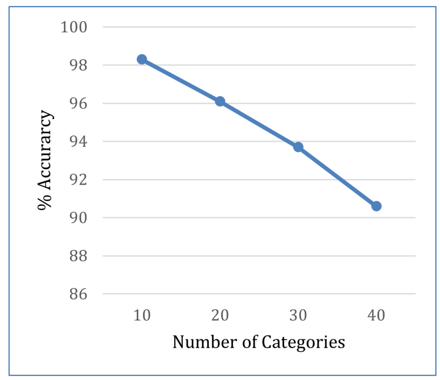

Figure 6. Effect of varying the number of categories on accuracy

A. *Classification using Deep Learning*

Shape-based classification approaches suffer from several challenges and limitations. In general, these approaches are useful only when the fruits and vegetables are photographed alone and preferably on a uniform medium or background. They are also not highly scalable as the accuracy tends to decrease for each new category of object added to the dataset. Thus, in this research, we have also investigated the use of deep learning neural networks for the classification of fruits and vegetables. We have used the TensorFlow open-source framework for machine learning [24]. The programming language used was Python and Anaconda as the development environment.

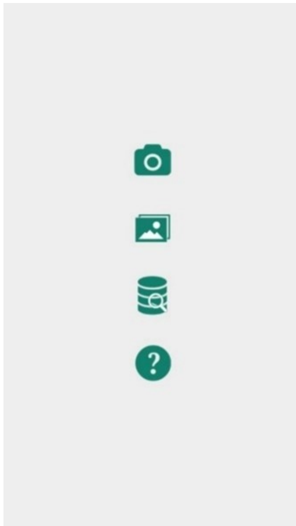

Figure 7. Welcome Screen

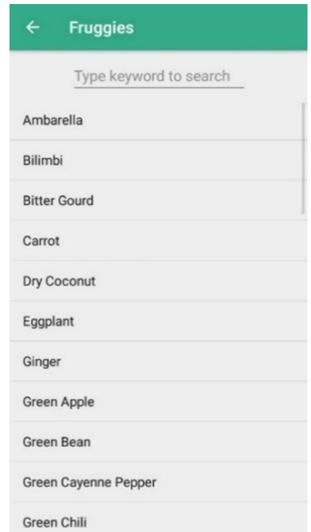

Figure 8. List of Produce

To assess the robustness of the deep learning neural network-based classifier, we augmented the original dataset of 1600 images with an additional 11200 images. These images were obtained by adding 20 units and 40 units of brightness to the original images, removing 20 units and 40 units of brightness from the original images, and rotating the original images by 90°, 180°and 270°, respectively. Thus, the total number of images in the dataset is now 12800 (8 x 1600). The default parameters were used for all experiments. An accuracy of 99.3% was obtained with the original 1600 images using a deep learning neural network with 2 hidden layers. An average accuracy of 98.1% was obtained using the deep learning approach while the traditional approach delivered an accuracy of only 81.0% when tested on 12800 images. This shows that deep learning neural networks works better that shape-based approaches and they are also more robust to changes in lighting conditions, scale, and orientation. They also perform well in the presence of distortions and occlusions.

Figure 7 shows the welcome screen for the FruVegy mobile app. There are four options. The first one allows a user to capture any image from their smartphone camera for identification. The second option allows the user to browse for a previously captured image from the phone's gallery. Selecting the third option will open another screen (activity) which displays the list of fruits and vegetables that are currently available for recognition. On selecting/touching an item from the list, another screen (activity) containing an image of this fruit/vegetable and its description will appear, as shown in Figure 11. The fourth option from Figure 7 shows a help option which contains all the instructions to use the app properly, as shown in Figure 9.

Figure 10 shows the captured image of an orange using the smartphone's camera. If the user is satisfied with the image, he can select the arrow on the bottom right corner of the screen to launch the recognition algorithm. If the image is not good, the user can discard it by selecting the cross at the bottom left corner of the screen. If the fruit/vegetable is correctly identified, it will open the corresponding screen (activity) which provides another image of that fruit/vegetable and its description. The nutritional values, such as the number of calories, its proteins, carbohydrates, fats, fibre, minerals, and vitamins content are also provided. The name of the fruit is provided in three different languages namely English, French and Mauritian Creole. The user can also hear out the name of the fruit/vegetable in these three languages.

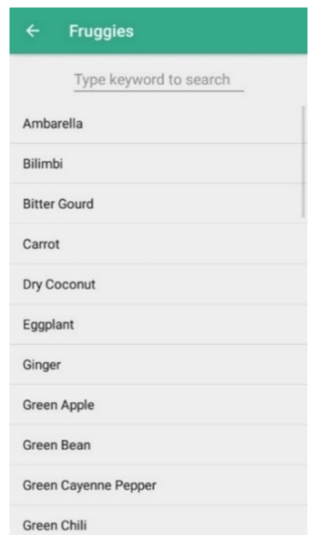

Figure 9. Help section

Furthermore, if the app is not able to identify the fruit/vegetable because of the bad quality of the image or because the fruit/vegetable is not found in the model, it

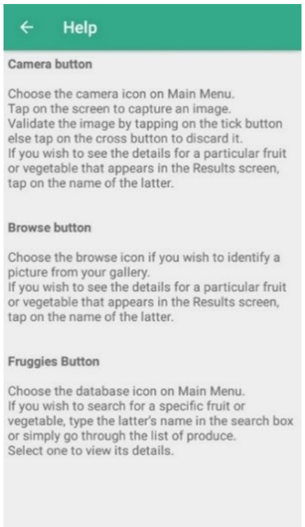

Figure 10. An Orange

Figure 11. Description of Orange

will display a message to inform the user that the object detection has failed and advises the user on how to take a good image.

B. *Performance Analysis*

The Tinycore app, which is available from Google Play, was used to monitor and measure CPU temperature, RAM usage and battery temperature [25]. The app is designed to be lightweight and offers a minimalistic design to minimise its energy consumption. Furthermore, Tinycore can handle multicore devices and is compatible with more than 99% devices running Android. It is free although advanced features are available for purchase [25]. The app was installed on four different mobile phones: Samsung Galaxy S4, Samsung Galaxy A5, Samsung Galaxy A7 and Samsung Galaxy J7, for performance analysis. The results are shown in Table

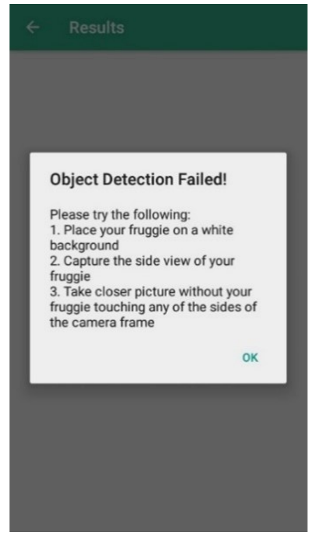

Figure 12. No known produce

TABLE IV. Performance Analysis

Feature	App not in use	App in use
CPU temperature	40^oC	43^oC
RAM used	65%	73%
Battery temperature	29^oC	31^oC

IV.

The initial battery levels for all the mobile phones were at 100% in all the experiments. The experiments in each smartphone were repeated five times and mean values were then calculated. The phones were recharged to 100% after each set of readings were taken and we waited 30 minutes before the next set of readings were taken, to allow the device to return to their normal working temperatures. We can see that there is an increase of 3% in the CPU temperature and an increase of 2% in the battery temperature when the app is in use. The actual % of RAM used depends on the size of the RAM. For J7, it is slightly more than the average as the RAM was only 1.5GB. For A8, it was much less than the average as the phone had a RAM of 4GB. The other two phones had a RAM of 2 GB. However, there is definitely an increase in RAM usage when the app is in use.

The app was used extensively for several periods of 30 minutes and the results were averaged to get the effect of the app on the battery level of the smartphones. The average decrease in battery level was 5% with the S4 model showing the highest decrease (9%) and the A8 model showing the smallest decrease (3%). Another set of tests was carried out by simply opening the app and leaving it idle. The average decrease in battery level was less than 2% in this case. The average time-taken taken to make a prediction if the phone's camera is used for capturing the image is 9 seconds. However, if the image is retrieved from the phone's gallery, the prediction is almost instantaneous. Based on the above statistics, we can safely say that the app does not have any significant negative impacts on the system's resources and that it can be used for a relatively long amount of time without draining the battery.

5. Conclusions

The aim of this research was to develop an Android-based application that would be able to acquire the images of fruits and/or vegetables, identify them and display their corresponding information. Our approach involves the capture of an image using a smartphone camera, its segmentation into a monochrome image, removal of noise using morphological operations, the subsequent extraction of colour, texture, and shape features and its identification using a machine learning model. The classifiers that were tested are neural networks, KNN, naïve Bayes, random forest, SVM, decision trees and deep learning models. The best performing traditional classifier was random forest with an accuracy of 90.6% on a dataset of 1600 images and 40 different classes of fruits/vegetables. To our knowledge, this is the largest number of categories that exists in literature today. Using deep learning, we were able to reach an accuracy of 98% under different testing environments. Moreover, this approach is more robust to changes in lightning, orientation, scale, distortions, and occlusions.

FruVegy will be helpful to school students to learn about fruits/vegetables and their health benefits. It will also be of interest to other researchers in the field of computer vision and artificial intelligence, to patients suffering from various types of medical conditions and to anyone who wish to follow a healthy diet or to learn more about the fruits and vegetables that are available in Mauritius. Furthermore, the near-perfect accuracy achieved using deep learning justify its use in relevant industries to identify fruits and vegetables and in automated check-out free grocery stores. Although the accuracy of the system is very high, there are still certain improvements that can be made to the system. Thus, in the future, we intend to create an even larger dataset with additional categories of fruits/vegetables and with more images per fruit/vegetable. More investigation will also be carried out with the parameters of the machine learning classifiers to find the best performing one.

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Anish Rao Appadoo is a Full Stack Web & Mobile Developer. He holds a bachelor's degree in BSc (Hons) Computer Science from the ICT Department at the University of Mauritius. During his 4 years of service in the development industry, he has acquired skills pertaining to accessibility, responsiveness, maintainability and optimisation. Additionally, he has coached trainees and been responsible for the development of multiple mobile and web applications. His latest works relate to building a private corporate ReactJS component library along with a team of UX and UI engineers.

Yashna Gopaul is a Software Engineer currently working closely with European developers to build a private video conferencing app for enterprise use. She is a graduate of the BSc (Hons) Computer Science programme from the Department of Information and Communication Technologies, Faculty of Information, Communication and Digital Technologies, University of Mauritius. She has four years of experience in Web and Mobile Application Development mainly on Javascript Frameworks.

Dr Sameerchand Pudaruth is a Senior Lecturer from the ICT Department at the University of Mauritius. He has a PhD in Artificial Intelligence (AI) from the University of Mauritius. He is a Senior member of IEEE, founding member of the IEEE Mauritius Subsection and has been a past Vice-Chair of the IEEE Mauritius Section. He is also a senior member of the Association for Computing Machinery (ACM). His research interests are Artificial Intelligence, Machine Learning, Data Science, Machine Translation, Computer Vision, Robotics, Mobile Applications, Web Technologies, Multimedia, Blockchain and Information Technology Law. He has written more than 70+ papers for national & international journals and conferences. He has been in the organising committee of many successful international conferences such as Africon 2013, IST Africa 2014, Africon 2015, AfriCHI 2015, ICCCS 2015, BigData 2015, DIPECC 2015, Africhi 2016, Emergitech 2016, NextComp 2017, ISCMI 2017, Mauritian Academic Conference 2018, icABCD 2018, Mauricon ICONIC 2018, icABCD2019, NextComp 2019, icABCD2020, Elecom 2020 and Mauricon ICONIC 2020. He has also written a book entitled, 'Python in One Week'. He is a reviewer for IEEE Access and Environment, Systems and Decisions (Springer) journals, amongst many others.

Appendix

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V	W	X	Y	Z	AA	AB	AC	AD	AE	AF	AG	AH	AI	AJ	AK	AL	AM	AN	
A	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	Ambarella
B	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	Bilimbi
C	0	0	35	0	0	0	0	0	0	2	0	0	0	0	0	0	0	3	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	Bitter Gourd
D	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Carrot
E	0	0	0	0	34	0	2	0	0	0	0	0	0	5	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	4	2	0	0	0	0	0	Dry Coconut
F	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Eggplant
G	0	0	0	0	1	0	38	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	Ginger
H	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Green Apple
I	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	Green Bean
J	0	0	1	0	0	0	0	0	0	34	2	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Green Cayenne Pepper
K	0	0	1	0	0	0	0	0	0	1	37	0	0	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Green Chili
L	0	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	Green Grape
M	0	0	0	0	0	0	0	0	0	0	0	0	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	Java Apple
N	0	0	0	0	0	0	0	0	0	0	0	0	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	Jicama
O	0	0	0	0	2	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	Kiwi
P	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	40	0	1	0	0	0	0	1	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	Lady Finger
Q	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Lemon
R	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	32	0	0	1	0	2	0	0	0	0	2	0	0	0	0	0	0	0	2	0	0	0	0	Lettuce
S	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	37	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	0	0	Lime
T	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Maize
U	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	36	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	Pear
V	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	34	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	Potato
W	0	0	3	0	0	0	0	0	1	2	0	0	0	0	0	0	0	1	0	0	0	0	32	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	Raw Banana
X	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	2	0	0	3	0	0	Red Apple
Y	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	39	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	Red Chili
Z	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	38	0	0	0	0	0	0	0	0	0	0	0	0	0	3	Red Grape
AA	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	40	0	0	0	0	0	0	0	0	0	0	0	0	0	Ripe Banana
AB	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	0	0	0	0	0	0	Sponge Gourd
AC	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	39	0	0	0	0	0	0	0	0	0	0	0	Star Gooseberry
AD	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	Strawberry
AE	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	39	1	0	0	0	0	0	0	0	0	Sweet Potato
AF	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	39	0	0	1	0	0	0	0	0	Tamarind
AG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	31	0	0	0	0	3	3	0	Tangerine
AH	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	33	0	0	0	0	0	0	Taro Root
AI	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0	1	0	2	0	0	0	2	0	0	0	1	34	0	0	0	0	4	Onion
AJ	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	27	0	0	0	0	Thai Eggplant
AK	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	34	1	0	0	Tomato
AL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	0	0	0	30	1	2	Nectarine
AM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	8	0	0	0	0	2	36	0	Orange
AN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	29	Peach

Figure 13