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PAPER

Biological Butterfly Characterization with Mobile System Using Convolutional Neural Network (CNN) Classify Image

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ABSTRACT

This study presents the development of a mobile identification system that detects biological butterfly characteristics through deep learning by capturing images. The challenge identified is that butterfly identification and recognition are difficult tasks because there are too many species, and it is hard to classify the types of butterfly species. Butterflies are also difficult to differentiate from each other, and limited studies are done using computer database referrals for butterflies' characterization. This study aims to develop an automated computer program to easily identify the species of butterflies. Deep learning in image processing is programmed, which can control the qualification, segmentation, and classification of images and automatically detect butterfly characterization. The design system consists of three stages: capture, feature extraction, and butterfly recognition. Then, multiple recognition clues such as shape, color, texture, and size are extracted and analyzed to analyze and recognize the butterfly. This approach is faster and less complex than the previous approach. The result successfully presents a convolutional neural network (CNN) to classify images after training and characterization. The graphics processing unit (GPU) that trains the image dataset presents 86% image accuracy in the allocated time. This research is significant in such a way that new butterfly species will be automatically collected and stored on the online server. The information could be treasured as a valuable butterfly database.

KEYWORDS

butterfly characterization, convolutional neutral network (CNN), deep learning, image processing, recognition, mobile application

1 INTRODUCTION

Butterflies are a member of the Lepidoptera order in the insect family, which is characterized by 1.5 million species in the world [1]. There are 170,000 butterfly species, and they are distinguishable from each other by their wing shapes, textures,

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and colors, which vary over a very wide range. Some of the very similar species can be identified by examining the external structures of the butterflies' genitals and internal organs, especially of the males [2]. Research has demonstrated that the butterfly species can be classified using image processing techniques and a machine learning method with high accuracy [3]. Throughout the past 70 years, research has examined the altitudinal range shifts of 30,604 lowland butterfly and burnet moth records from 119 species in the federal state of Salzburg in northern Austria. It covers an altitudinal gradient of more than 2,500 m. The research has compiled species-specific characteristics related to the ecology, behavior, and life cycle of each species. The average butterfly occurrence as well as the upper and lower occurrence limits >300 m uphill have changed during the study period. In the last 10 years, they have seen a particularly noticeable change where the strongest shifts were seen by sedentary and habitat-specialist species, while habitat-generalist and mobile species showed the weakest shifts [4].

A prototype was developed to characterize biological butterflies using a mobile system that can classify the butterflies' characteristics. This system includes advanced imaging technology and an integrated measurement algorithm, all presented in an easy-to-use, user-friendly interface. Good visibility of butterfly features such as shape, color density, texture, and size is essential for classifying certain butterfly species, which is why an image of the butterfly is captured. Then, image classification was programmed that uses the spectral data represented by the binary numbers in one or many spectral bands to try to differentiate each of the captured image's pixels based on the available spectral information [5]. These features are then extracted and compared to the data stored in the database. Depending on the accuracy of the image's recognition and classification, the final resolution is generated by the system [6]. Butterfly species are frequently distinguished in terms of their shapes, textures, colors, and sizes for them to be recognized and classified according to their respective species. The convolutional neural network (CNN) classification technique with deep learning features is utilized to recognize the butterfly's shape, size, color, and texture with just a click of an image capture [7].

There are approximately 170,000 butterfly species, and they are distinguishable from each other by their wing shapes, textures, and colors, which vary over a wide range. The problem is that there are too many species, and it is difficult to classify the type of species. One identified piece of research has presented that the identification of species can also be done by molecular-level studies [8]. Usually, to determine butterfly and moth species, analysis of genital characters is also important [9]. Traditionally, to determine the species of a particular butterfly, its genital characteristics have to be extracted using specific chemical solutions for manual experimentation using molecular techniques or by preparing genital slides through certain processes and methods that are very time-consuming and costly [10]. This study provides an alternative to the traditional procedures for identifying butterfly species by utilizing the deep learning features provided by CNN image processing.

This study presents the development of biological butterfly characterization with a mobile system. The system can determine the species of butterflies simply by analyzing the image captured by the smartphone. Butterflies can be found all over the world and in various types of habitats: humid and dry, cold or hot, high in the mountains, or as low as the sea level. It is estimated that there are around 170, 000 butterfly and moth species around the world. There are approximately 28,000 types of butterfly species worldwide, while the rest are moth species [11]. It is difficult to distinguish the different species because the variety of different species is too large. This system can significantly help determine the butterfly species and geographical location. This automatic method is also relatively faster and less complicated than any other traditional approach. This study presents a CNN-classified image after training and its characterization. The GPU that trains the image dataset presents an 86% accurate image in time.

There are too many species, and it is difficult to classify the type of species. The objective of this system is to design a biological butterfly characterization mobile system by comparing the captured image with the learned image from the data set and to identify butter on the live system using mobile at any condition that is either flying, resting, open, or close wings, whether upper or underside.

2 LITERATURE REVIEW

Research in Malaysia shows that birds and butterflies are used as ecological indicators because they are relatively easy to identify and show clear responses to environmental change. Pearson's correlations and multiple regressions, followed by an analysis of Akaike's Information Criterion, were conducted to study the relationships between the measured variables and to identify which of the variables have a significant effect on bird and butterfly species richness and abundance [12]. Butterflies are often used as indicator surrogates to evaluate the quality of ecosystems. This is made possible due to their sensitive responses to environmental fluctuations and habitat changes. Studies have presented a checklist of butterflies in the hills and evaluated habitat suitability to support the proposal to gazette the hills as part of the Gunung Ledang protected area in Malaysia. A total of 60 individuals belonging to 23 species, 21 genera, and five families were recorded [13].

Deep CNNs have led to a series of breakthroughs in image classification [14]. A computational model, which usually consists of numerous processing layers, would be able to learn about the data representations at various abstraction levels by using deep learning in CNN [15]. Such approaches have been proven to drastically improve the accuracy of various visual recognition systems [16]. Image classification is the process of taking an input image and then classifying the output image by the predetermined or desired type of characterization. Human beings have the skills to recognize and quickly identify the environment as well as the objects surrounding them. These skills of being able to instantly recognize patterns, generalize from prior knowledge, and adapt to different image environments are ones that the machine does not have. The computer acts on images as inputs when it is scanning or looking for an image, and the computer can automatically establish those images in an array that consists of pixel values. An array of $32 \times 32 \times 3$ number dimensions, like 3 = RGB values, is seen depending on the resolution [17] and size of the input image [18].

Image processing is defined as the process of extracting the features of the input image or series of images and videos and performing some recognition operation on them. Image processing can produce an output of what the image is, and all the procedures are executed automatically using a computer or artificial intelligence [19]. Generally, universal image-processing techniques apply a standard signal-processing technique and treat the image as a 2-dimensional signal. The image may be declared as a 2-D function of f(x, y), where x and y are the image's coordinates on a 2-D plane, and the 'f' amplitude at a specific coordinate is referred to as the concentration of the image at that particular position [20]. The keyword 'gray level' usually refers to the intensity of a particular monochrome input image.

Images are generally formed by some combinations of respective images for images with multiple colors. Multicolor images are made up of the three monochrome-based images, which are R (red), G (green), and B (blue), also known as primary or component images. The importance of RGB colors related to the camera on a mobile phone that captures certain images for processing, such as the recent mobile app augmented reality research development [21]. This is why the typical techniques that were used for monochrome images are further applied to process multicolor images by working on the three basic-colored images separately. It is suggested that object shapes generally contain more information despite their appearance properties; for example, texture and color can vary between object instances rather than the shape.

In another aspect, image texture is specified as a series of metrics that are computed in the procedures of image processing, devised to calibrate the obtained texture's composition of the input image. The textures of an image provide the information needed by the system regarding the arrangement of colors or saturations in particular input images or the specified region of the image in question. This technique has recently been used in many augmented reality system designs [22]. The textures of an image are usually found in natural scenes captured in the image, or they can be artificially generated by using specific algorithms. The texture of an image is a very significant factor or element in image recognition or image classification. A structured approach and a statistical approach can be chosen to analyze an image texture in digital processing accurately.

3 METHODOLOGY

This study flow consists of three main phases: the analysis phase, the design phase, and the development and testing phase of biological butterfly characterization with a mobile system.

3.1 Flowchart

Figure 1 illustrates the study flowchart. Hardware and software experimentation are executed to characterize and analyze the crucial parameters to be used in the research's design system. The components used in this system are a smartphone, a computer, and a GPU. The smartphone functions as a user interface, and the computer acts as a server. The GPU is used to train the butterfly image. The software used in this study includes Microsoft Visual Studio Community, Android Studio, MATLAB, and XAMPP. With these vital components, the processes of identifying the parameters of the research are executed. The parameters of the input fed to the system are then identified and analyzed using the chosen algorithm. Next, the dataset image of the butterfly is collected and compiled. Images of butterflies are trained into a CNN on a GPU. The learned images and captured images are compared to determine the butterfly species after processing and analyzing the images. Then, once the system functions are obtained and the desired features are achieved, the study can proceed to the final development stage, which is the development of the smartphone application and a server for it to access the prepared database. The database is developed by utilizing the features of XAMPP software. The Butterfly Characterization mobile application was then developed using Android Studio.

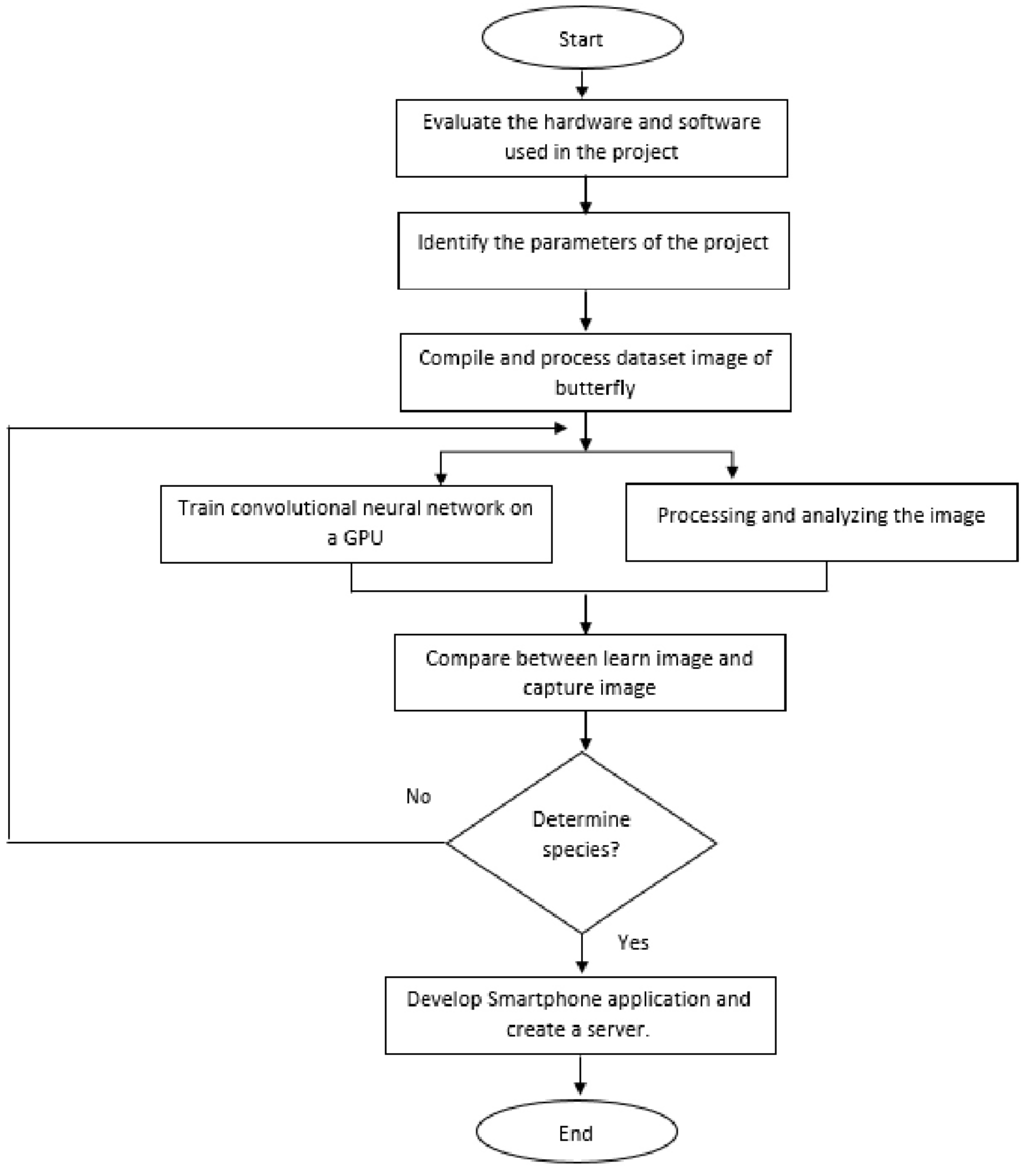

Fig. 1. Flowchart of the system

3.2 Block diagram

This study uses several classification techniques. Biological butterfly characterization with a geographical mobile system uses images to recognize, analyze, and process, based on deep learning image processing [23]. Figure 2 illustrates the functional block diagram. A learned image of a butterfly needs to be stored on the database server. The images of butterflies need to be converted into a dataset. The network on the server data needs to be trained before the processed image is stored on the database server. The database can contain over a hundred annotated images from a total of over 14 species of butterflies. Then, the process of capturing the image of the butterfly is processed and analyzed by comparing the captured image and the learned image from the database server to determine butterfly species after capturing the recognition image of a butterfly. Lastly, the results of the biological butterfly characterizations will be sent to the mobile system.

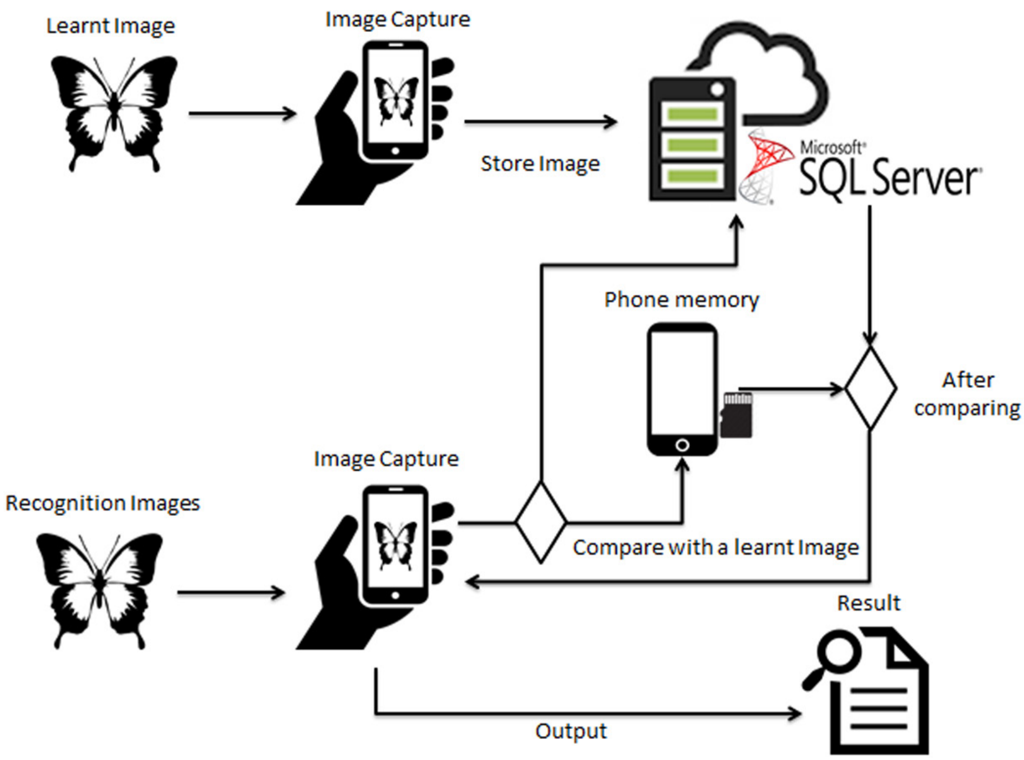

Fig. 2. Block diagram of the butterfly recognition system

3.3 Convolution neural betwork

Figure 3 below shows the images of butterflies trained in the CNN. CNN is a type of artificial neural network that falls under the category of feed-forward. This means that the organization of the butterfly's external structure would trigger the patterns' connectivity in the neural network.

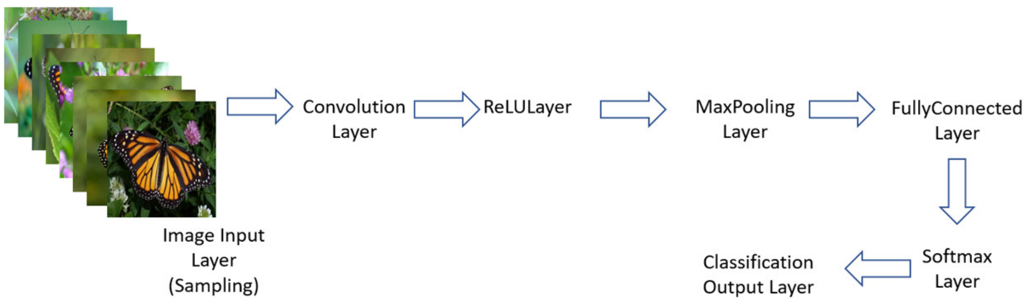

Fig. 3. Structure of the convolution neural network

The CNNs consist of receptive fields with multiple layers. Receptive fields are small groups of neurons that function to process chunks of the input image. The convolutional layer is the major component of a general CNN. The parameters of a convolutional layer have a set of trainable filters, also known as kernels, that provide a small receptive field that can extend over the entire input volume. Each of the filters is convoluted through the whole volume of the input, where the product between the filter's entries and the system input is computed, producing a

2-D activation map of the used filter. The next operation is where the neural network will learn the activated filters when some features are detected at some position in the data obtained from the provided input [20]. Another crucial part of CNN is pooling. Pooling is a type of down-sampling used for non-linear processing. The non-saturating activation function is performed by a layer of neurons called rectified linear units (ReLU). This ReLU layer of neurons enhances the decision function's nonlinear components and the whole network with zero negative effects on the convolution layer's receptive fields, as calculated from Equation 1. The loss layer, on the other hand, is normally the final layer in the neural network, which determines how the training of the network penalizes the difference between the predicted labels and the real ones.

$$f(x) = \mathrm{Max}\ (0, x) \tag{1}$$

3.4 Deep learning image process

This study presents a system that uses CNN to determine the species of butterfly. Deep learning image processing is used instead of using standard image processing because standard image processing is not powerful enough to classify the butterfly species [24]. CNN consists of a few structural layers [25]. Figure 4 shows the CNN structure level. CNNs consist of several layers for feature extraction and classification, one of which is the convolution layer. This layer serves as a feature extractor that extracts important information from the image.

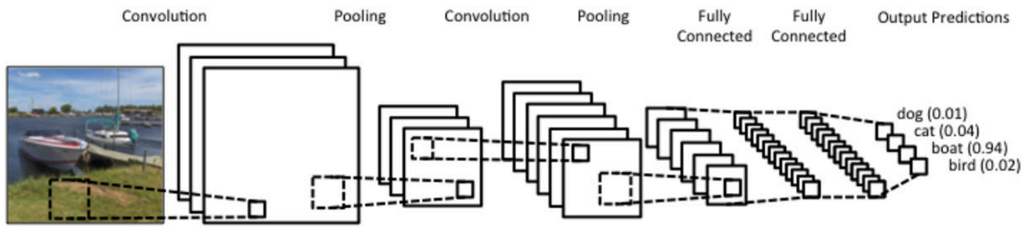

Fig. 4. Convolutional neural network layer

- Rectified linear units

The ReLU is the layer of neurons used to optimize the use of CNN's non-saturating activation function. It decides whether a particular unit fires or stays dormant. It is used directly after the convolution layer. On the other hand, the pooling layer uses a kind of non-linear downsampling, which can reduce an initially massive feature set into a much smaller one. This layer is important to reduce the computational overhead for training and classifying data.

- Fully connected layer

The fully connected layer has some clear similarities to the multi-layer perceptron (MLP). It performs the classification of the previously extracted features using the trained weighted connections. The SoftMax layer, on the other hand, functions to consolidate and present the final output to the user. Figure 5 presents the GPU that was used over the central processing unit (CPU) because of its higher speed and competency in training the convolutional neural networks by using GPU computing.

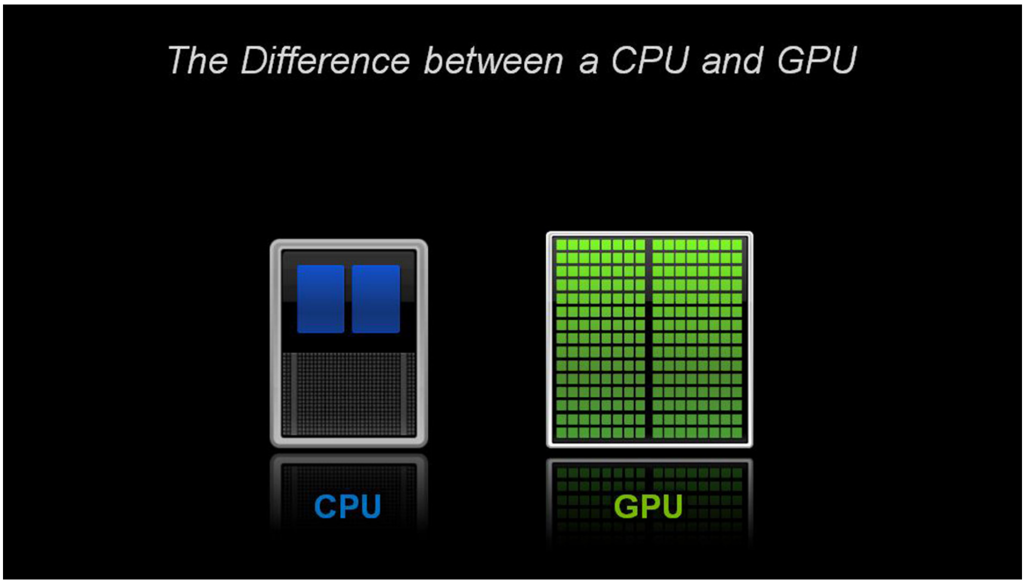

Fig. 5. GPU and CPU

4 RESULTS AND ANALYSIS

The obtained results show that a system based on a convolutional neural network was successfully developed. Figure 6 shows the classified image after the CNN is trained. It shows the captured image of the butterfly can be determined using CNN by analyzing it to classify and recognize the butterfly.

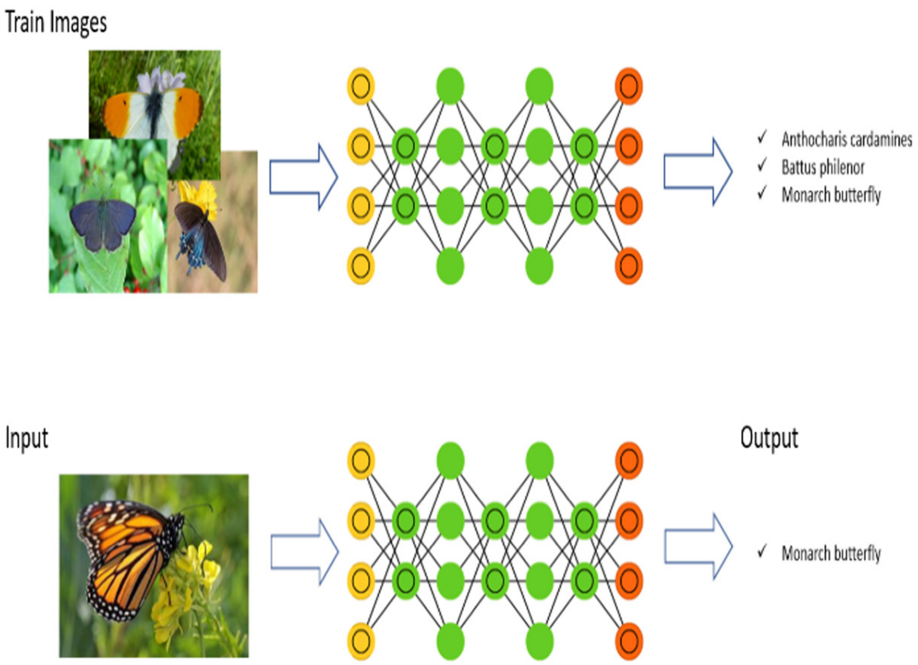

Fig. 6. Classification and recognition of an image

Figure 7 shows the Butterfly Characterization App Interface. Clicking the camera logo will take the user to a function related to cameras. The application allows the user access to a camera so that they can snap images of butterflies alongside it. The smartphone's user gallery logo leads the user to a gallery. To determine the species, the user can click on an already-existing image of a butterfly stored in memory. By clicking the upload logo, the image is uploaded to the server and examined. Figure 8 shows the captured image of a butterfly. The application gives a user permission to access a camera, whereby the user can use a camera to capture a butterfly image.

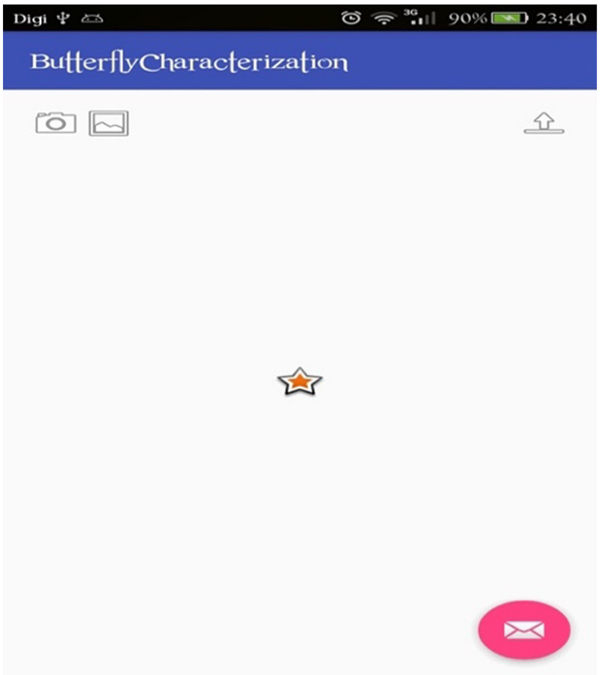

Fig. 7. Butterfly characterization apps interface

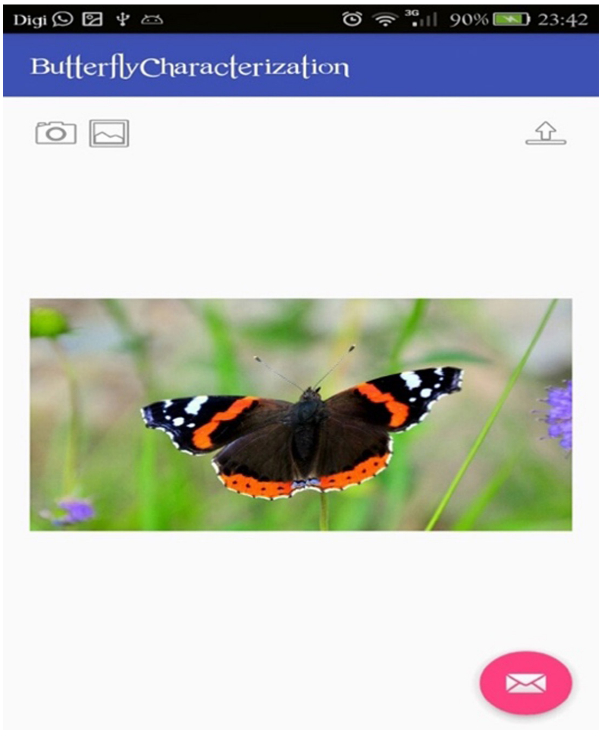

Fig. 8. Capturing image of butterfly

Figure 9 shows the captured image of the butterfly being uploaded to the server to be analyzed and processed to classify and recognize the butterfly. The user can also select an image from the gallery to upload to the server. The process took some time for the image of the butterfly to be uploaded onto the server.

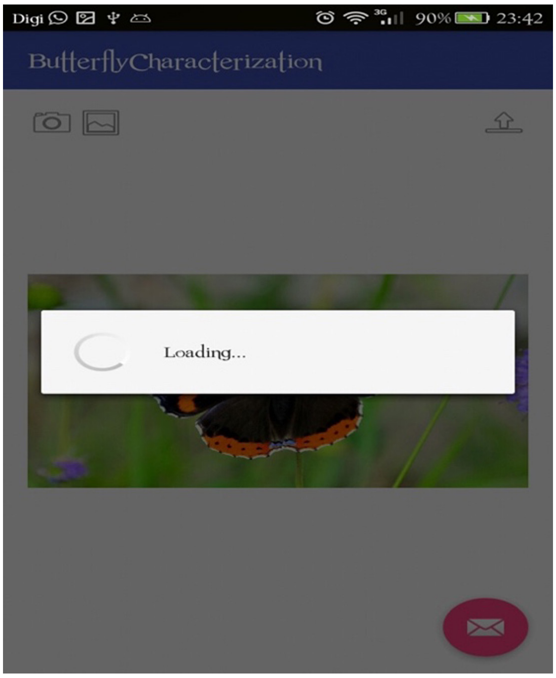

Fig. 9. Uploading the image

Figure 10 shows the resulting capture of the image of the butterfly after it has been analyzed and processed using CNN. The type of species identified from the capture is the Vanessa Atlanta butterfly.

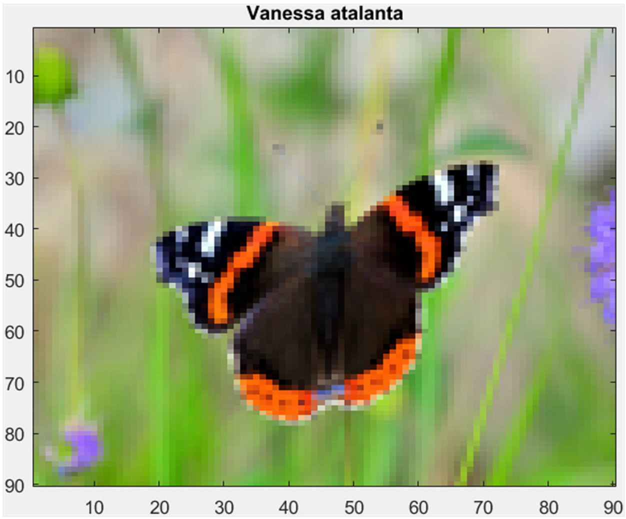

Fig. 10. Recognition of the image

Figure 11 shows the GUI for biological butterfly characterization. The image of the butterfly is being loaded into the system to be analyzed and processed to classify and recognize the butterfly. The process took some time for the image of the butterfly to be classified.

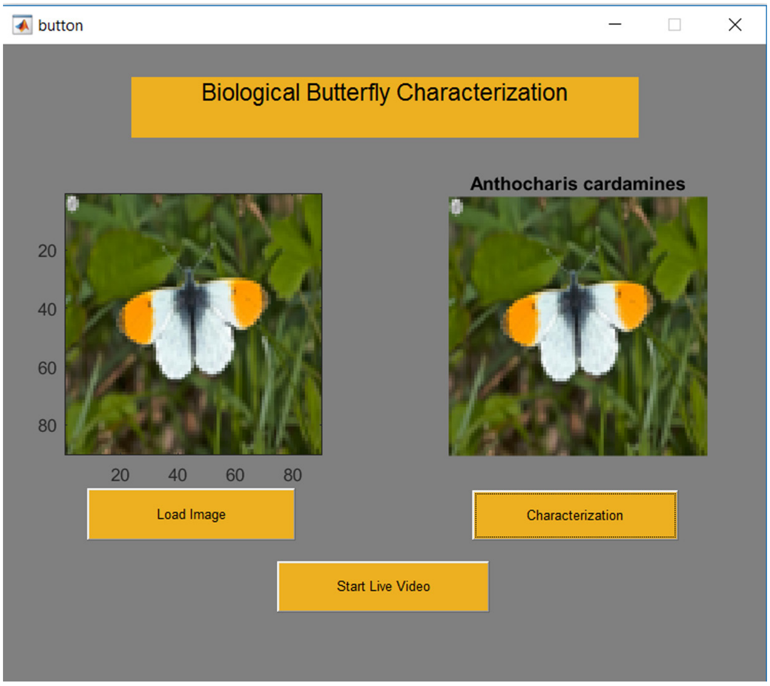

Fig. 11. Graphical user interface

Figure 12 shows the result presenting the difference between a graphics processing unit (GPU) and a CPU. The CPU only has multiple cores, while the GPU consists of thousands of cores. A CPU is integrated by only a few cores that are designed for sequential processing; meanwhile, a GPU comprises a mostly parallel organization consisting of thousands of much smaller but far more efficient cores that are optimized for processing multiple processes in parallel. Figure 12 shows the graph of the time taken for a GPU to train the image dataset.

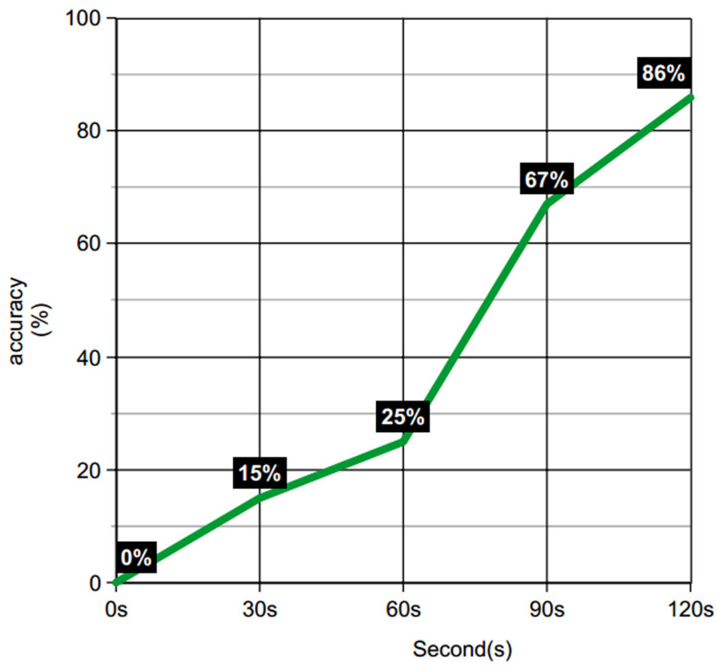

Fig. 12. Time taken GPU to train Image

Figure 13 shows the graph accuracy of the validation data versus the training set size. The graph displays the result, and it can be concluded that the size of the data set used for training the image affects the accuracy of the validation data. The larger the size and quantity of the image of the butterfly, the more accurate it will be on the validation data. The problem when training a large quantity of images is that they need to be trained using a very powerful GPU.

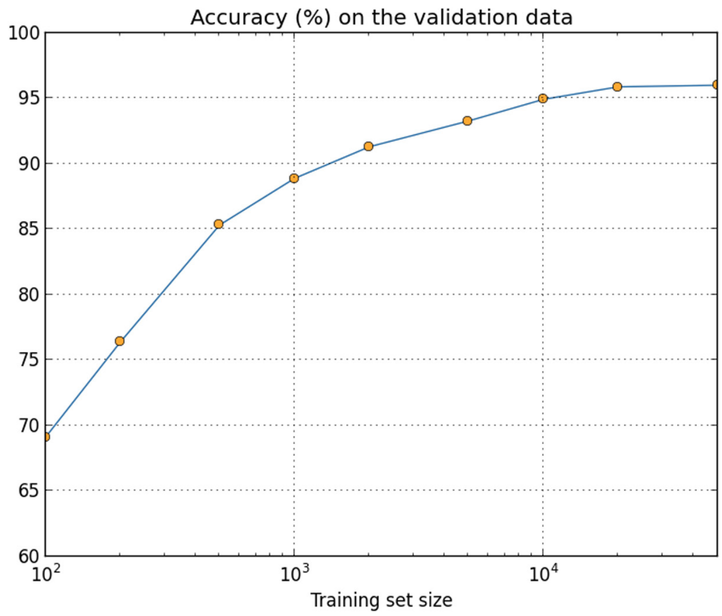

Fig. 13. Graph (%) accuracy on the validation data

5 CONCLUSION

In conclusion, this study has been completed to develop a mobile app that can authenticate the biological butterfly characterization. It is an efficient alternative method that is much faster in time and more cost-effective compared to the traditional identification of butterfly species. This developed system can be utilized for butterfly characterization by automatically distinguishing the external qualities of the butterflies in terms of their sizes, shapes, colors, and surface textures. As deep learning image processing is a very complex process, the proposed system may not be able to achieve 100% accuracy in species recognition. Keeping this in mind, from the initiating process on, the user interface will be constructed accordingly to make up for its weaknesses. Currently, classification, localization, detection, and segmentation are the best features achieved for this system, which are the ones that greatly contribute to providing reliable recognition. This is achieved through the process of taking an input image and producing an output in the form of a class number out of a set of categories. Automated classification provides valuable functions in determining the different species of butterflies all around the globe.

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