Image Recognition of Different Hamster Breeds Using Convolutional Neural Networks

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***Abstract*— Hamsters exhibit a variety of breeds, making breed identification challenging at first glance. This study proposes a solution using Convolutional Neural Networks (CNNs), specifically VGG16 architecture, to aid pet owners in distinguishing between hamster breeds. Researchers developed an image capturing system and a web application where users can upload hamster images to receive breed identification. The system focuses on recognizing the four most common hamster breeds: Campbell, Roborovski, Syrian, and Winter White, utilizing the VGG16 model trained and tested on a dataset collected by the researchers. The implementation involved a Raspberry Pi 4B with 4GB RAM and a webcam housed in a specially designed box for image recognition of hamsters. Evaluation using a confusion matrix demonstrated an overall accuracy of 91.67%, indicating the effectiveness of the proposed system in identifying hamster breeds. This research contributes to the development of accessible tools for pet owners and enthusiasts interested in hamster breed identification.**

Keywords—VGG16, Convolutional Neural Network, Raspberry Pi, confusion matrix, image recognition

I. INTRODUCTION

Every species has its different kinds of breeds. For instance, domestic dogs have golden retrievers, labradors, huskies, poodles, and more. Hamsters as species, also have different kinds of breeds, but based on their physical appearance, they may be difficult to distinguish at first glance especially for the people who know less about hamsters. Unlike dogs, their breeds are easily discernible because of certain factors such as fur color, facial structure, body shape, size, and their behavior. An existing research, implemented a system designed to recognize dogs through their nose prints as biometrics [1]. In the case of hamsters, usually, one can tell the breed by looking at the patterns in the hamster's facial structure aside from observing their size and fur color. So, one must be knowledgeable first for people to tell the breed of a hamster. In the subject of keeping them as pets, the domestication of hamsters became a trend due to how easy they were to keep and breed. In contrast to their sightings in pet shops and labs, their sightings in the wild have been steadily declining due to industrialization and urbanization. One of the most common pet breeds, Syrian hamsters are now considered vulnerable in the wild nearing endangerment due to the risks of these environmental factors [2]. Hamsters are not that adaptable to their environment in comparison to other domesticated animals. These domesticated hamsters are kept in captivity and are usually bred in herds in pet shops and livestock facilities for preservation. Their environment in these facilities is less than ideal as the effect of these solitary creatures being confined in a single cage together places stress on these animals. Living conditions of these domesticated animals can improve by educating pet owners about their different dietary needs and to enrich the environment of a specific breed of hamster suitable to their natural behavior [3]. The convolutional neural network is a kind of multi-layer perceptron which is designed for two-dimensional image recognition as a deep learning algorithm, and each kernel in different layers is learned spontaneously [4]. CNN offers a higher success rate for image recognition than other image classification methods due to its proficiency in image representation [5], which explains a lot of research involving image processing and recognition utilizing CNN. A related study concluded that CNN was able to reach a high accuracy rating for determining sample damage types in corn [6]. CNN was also able to classify and count White Blood Cells based on microscopic blood images [7]. Another study utilized CNN for detection of corn leaf diseases with the implementation of OpenMP which was a main factor for attaining high accuracy in classifying leaf diseases with Raspberry Pi [8]. The performance of the whole network can be improved by increasing the number of samples. CNN is mostly used in studies that involve image recognition [9]-[15]. While gathering and studying related literatures, the researchers have found out that there is no image capturing system designed for identifying different breeds of hamsters yet. Although previous studies such as the rare animal image recognition based on CNN used CNN to train the system to identify rare animals only [4]. Specifically, a VGG16 architecture is used for the system. Among the various deep learning architectures available for image classification, VGG16 has become one of the most popular choices [16]. Studies that are related to image detection, recognition, or classification have used VGG16 as their main architecture [17]-[20] The main objective of this research is to identify different hamster breeds using transfer learning method and Convolutional Neural Networks. The specific objectives are as follows: (1) to develop an image capturing system that will capture images of different hamsters, (2) to utilize Convolutional Neural Network for the device to identify specific patterns that would lead to the recognition of the details on hamster breeds via Raspberry Pi 4, and (3) to evaluate the findings of the system using Confusion Matrix. The research will provide insights in recognizing hamster breeds for pet owners and breeders to understand a hamster's traits and quirks by their genealogy. Through this research will be able to extrapolate information on a particular breed of hamster's behavior. The research may also help pet owners to prevent inbreeding as well as prevent health risks that are prone to specific breeds. The dataset that will be used to train the program will only cover images of hamsters that are kept as pets, it will not cover and recognize

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species that are found in the wild or animals in the same order of rodents. Four breeds will only be included in the dataset: (1) Campbell, (2) Roborovski, (3) Syrian, (4) Winter White. And in each breed, the researchers will only collect 600 images, making it a total of 2400 images. The images will only come from the researchers themselves and some of the images will be taken from the web. Lastly, the main hardware that will be used is Raspberry Pi 4 Model B with an 4GB memory.

II. METHODOLOGY

A. Research Methodology

The researchers will use the research methodology detailed above to create an efficient and robust system for identifying hamster breeds using the VGG16 convolutional neural network model. The proposed system will identify Campbell, Roborovski, Syrian, and Winter White breeds. High quality images will be taken by the researchers or collected through various reputable sources ensuring a comprehensive dataset. Each image will be manually labeled before undergoing preprocessing steps, including removing duplicates and low-quality images, augmentation, and resizing to match the input requirements of the VGG16 model. The model will be pre-trained on ImageNet and will be fine-tuned for hamster breed classification by calibrating its top layers and replacing its final fully connected layers to match the amount of target breeds.

The dataset will be split into training, validation, and testing sets and will be trained on the appropriate hyperparameters with early stopping and model checkpoints to avoid overfitting and to keep the model's performance optimal. The model's accuracy and precision will be evaluated and will be visualized through a confusion matrix, cross-validation will further ensure the robustness of the model. The model will be deployed in an application, allowing users to upload and capture images and receive breed predictions.

The researchers will focus on optimization post-deployment and the summarization emphasizing the effectiveness of VGG16 model for classification tasks and potential improvements will be discussed for further improvements.

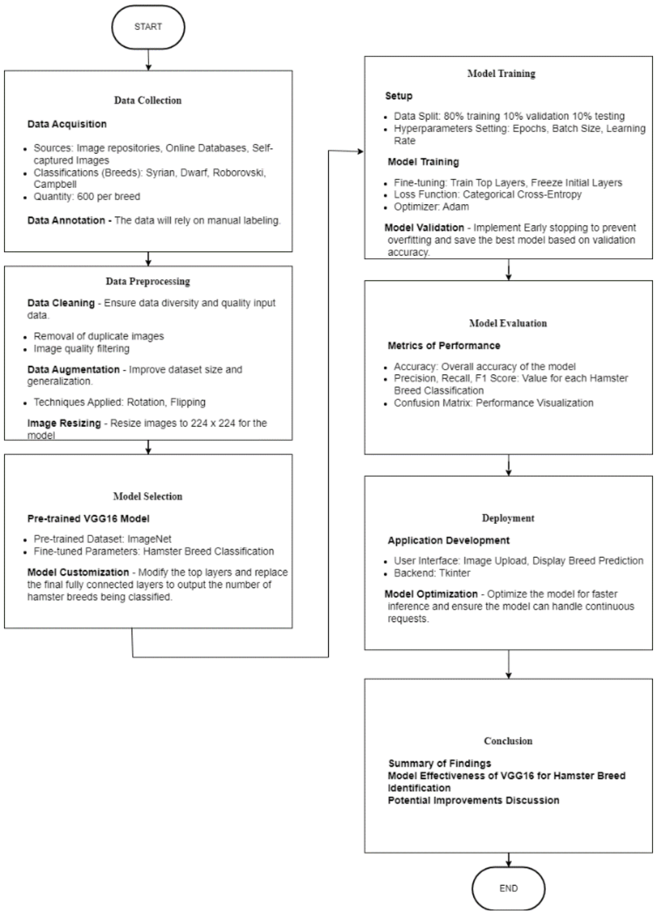

Fig. 1. Research Methodology Flowchart

B. Conceptual Framework

The conceptual framework of the study as shown in Fig. 2 will input an image of a random hamster either through the system’s camera, it will serve as an input data of the system for the recognition process. The data and its parameters will be pre-processed through the VGG16 architecture, passing through its several convolutional and connected layers to extract features and patterns. The model generates bounding boxes and refines it to align with the detected image better. It will then classify what kind of hamster breed it is through the four types it will recognize and the results of the system will be shown in the LCD screen after processing the data of the image

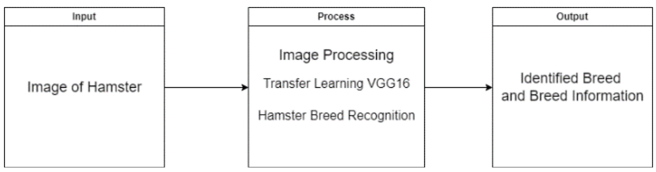

Fig. 2. Conceptual Framework

C. Hardware Development

Fig. 3 shows the hardware block diagram of the proposed system. It uses Raspberry Pi 4B, a single board computer as its main system unit to process the input and output of the proposed system. It uses an SD card as its storage to store the operating system and the training model along with the

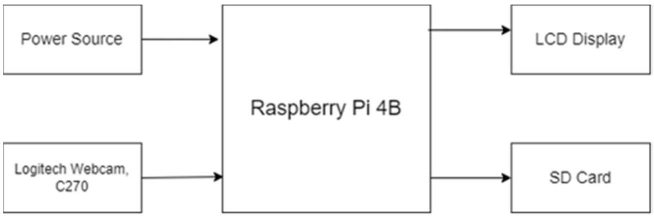

Fig. 3. Hardware Block Diagram

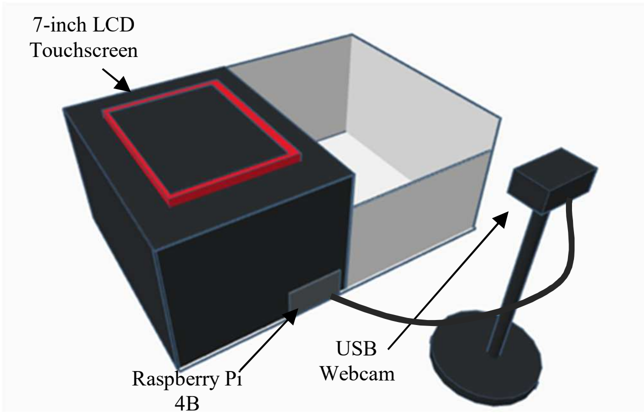

Fig. 4. Prototype and Its Components

dataset. The webcam captures images that will be classified into one of the four different breeds. The outputs and results will then be displayed on the LCD screen.

Fig. 4 illustrates the construction of the prototype and its components. The system consists of a box with a prominent white space and attached hardware components. This white space is designed to accommodate the hamster, allowing users to capture images while the hamster is inside. The screen is mounted on top of the box, and the Raspberry Pi is positioned on the side, with its Ethernet and USB ports exposed for peripheral connections. Additionally, the USB webcam is attached to a handheld stand. This setup allows the users to freely maneuver the webcam in order to get a desirable angle in capturing the hamster's image, since the hamsters will usually move around the space provided.

D. Software Development

The system flowchart as shown in Fig. 5 starts with the device capturing an image of a hamster in the device's open housing and the movable webcam. The VGG16 model will take the image input and adjust its aspect ratio if it doesn't fit the network architecture. It is then passed through convolutional layers to extract its features and patterns hierarchically. It is then flattened and passed through connected layers to classify the image into four different breeds. The model then converts these data into raw class scores and the rates indicate its confidence level that it is the predicted class for the input image. It is displayed on the LCD screen of the system.

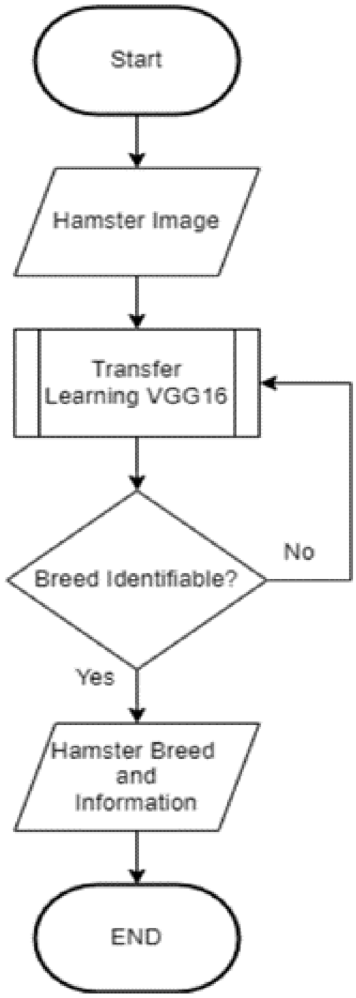

Fig. 5. System Flowchart

The hamster breed identification system is consolidated into a single application, as illustrated in Fig. 6, which shows its graphical user interface (GUI). The application is developed in Python, utilizing several libraries to ensure its comprehensive functionality. Firstly, the framework 'Tkinter' is used to create the GUI, responsible for generating widgets such as buttons, labels, frames, and dialogs. To enhance the visual appeal and functionality beyond what standard Tkinter offers, the 'customtkinter' library is employed. This library provides advanced widgets and customization options that enrich the user experience. Additionally, the OpenCV library is integrated to incorporate computer vision capabilities. OpenCV enables the system to capture images from the camera, perform real-time video processing, and apply various image transformations, thereby enhancing the application's overall performance and accuracy.

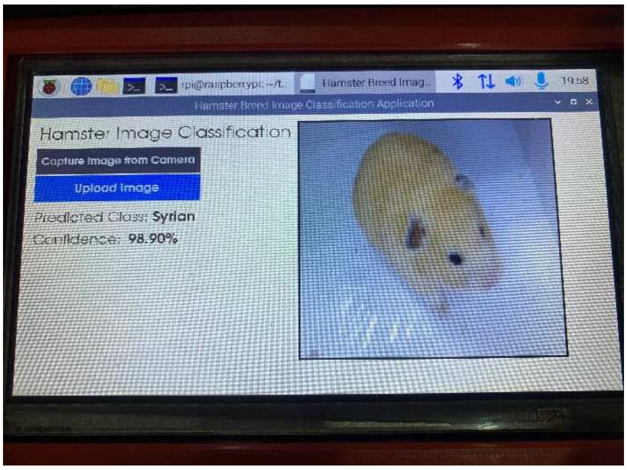

Fig. 6. GUI of the Application

E. Algorithm Creation

The model was trained using an RTX3070 GPU. The dataset consists of different hamster breeds. The model has four classes: Campbell, Roborovski, Syrian, and Winter White. The entire dataset consists of 2400 images, all in all, 600 images for each class. The amount of image set will be split 80-10-10 among training, validation, and testing respectively. The training dataset consists of 1920 images, 480 images for each class. The validation and testing dataset consists of 480 images all in all, 240 images each, and 60 images in each class in validation and testing. The images that were used for training and validation and were captured in a specific confinement where the surface and walls were colored white. Fig. 7 shows the different hamster breeds that will be learned by the model. The images were taken by the researchers themselves. The model was trained using VGG16 architecture for 50 epochs. After training the model, it will be tested using the provided test dataset.

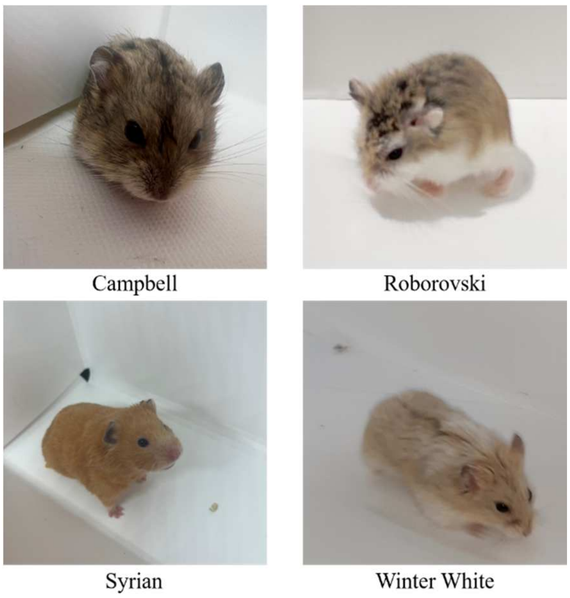

Fig. 7. Images of the different hamster breeds

F. Model Training

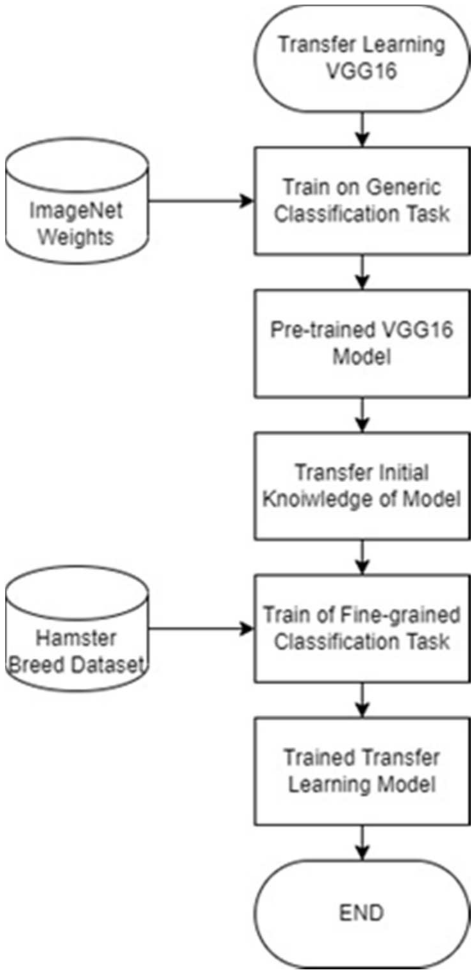

Fig. 8. Training Flowchart

The training flowchart of the algorithm is shown in Fig. 8, it shows the process of the data being captured individually in a controlled environment. The researchers took care of two different hamsters each breed and captured the data with a lightbox on a white background to make the training of the dataset focus on the hamster's features. These data are then labelled and split into four different class. The created dataset will include Campbell, Roborovski, Syrian, and Winter White. The dataset will be pre-processed and augmented with Keras utilities to better accommodate the VGG16 architecture. The system uses transfer learning of VGG16 with Imagenet training weights to reduce training time and generalization. The pre-trained model's generical classification will be trained on the dataset the researchers created so it could be do well on fine-grained classification tasks. The new model will be loaded without the output layer and the first few layers frozen so it retains some of its knowledge and then train the subsequent layers for the specific task of identifying hamster breeds.

III. Results and Discussions

Upon completion of the model training, the metrics of the newly trained model are shown Table I. The model stopped its training at the 50th epoch. It has achieved a training accuracy at 0.9620 or 96.20% and a validation accuracy at 0.9792 or 97.92% while having a training loss at 0.2330 or 23.30% and a validation loss at 0.1874 or 18.74%.

TABLE I. VGG16 MODEL METRICS TABLE

Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
50	0.9620	0.9792	0.2330	0.1874

Table II shows the confusion matrix as a result of testing the model. The testing phase consists of 240 images in totality, 60 images per class. The accuracy for each class in this testing phase will be computed using the following formula as shown in (1).

$$\%\text{accuracy single breed} = [TP / \sum \text{no. of samples}] * 100 \quad (1)$$

The percentage accuracy of a single breed is defined by its True Positives (TP) divided by its total number of samples times 100. The formula will be used four times since there are four existing classes. To get the overall accuracy of the model, the four individual accuracy percentage will be averaged times 100. The formula is shown in (2).

$$\%\text{Overall Accuracy} = [\sum \%\text{accuracy each breeds} / \sum \text{no. of classes}] * 100 \quad (2)$$

Using the provided test dataset, the results were analyzed and are as follows: 55 true positives for the Campbell breed, 53 true positives for the Roborovski breed, and 56 true positives each for both the Syrian and Winter White breeds. To determine the individual accuracy of each breed as well as the overall accuracy, Equations 1 and 2 were applied, as shown in Table III. The Campbell breed achieved an accuracy of 91.67%, the Roborovski breed had an accuracy of 88.33%, and both the Syrian and Winter White breeds each had an accuracy of 93.33%. This results in an overall accuracy of 91.67% across all breeds.

TABLE II. CONFUSION MATRIX OF HAMSTER BREEDS WITHOUT NORMALIZATION

		PREDICTED LABEL			
		Campbell	Roborovski	Syrian	Winter White
TRUE LABEL	Campbell	55	2	3	0
	Roborovski	1	53	1	5
	Syrian	2	0	56	2
	Winter White	2	1	1	56

TABLE III. TABLE FOR THE ACCURACY OF EACH HAMSTER BREEDS

HAMSTER BREEDS	**ACCURACY (%)**
Campbell	91.67%
Roborovski	88.33%
Syrian	93.33%
Winter White	93.33%
OVERALL ACCURACY	91.67%

IV. CONCLUSIONS AND RECOMMENDATIONS

Identifying Hamster Breeds using VGG16 focuses on developing an image capturing system and a software that delivers accurate identification of hamster breeds. The objectives of the study are completely achieved. The system is developed with hardware components such as the Raspberry Pi 4 and a Webcam Camera to capture the images of the hamsters, input it into the model and successfully identify its breed and indicate its output on an LCD display. A custom dataset consisting of 2400 images in total was used for training, validation and testing of the model and a confusion matrix was used to determine the accuracy of the new model. The model has shown to be 92% accurate overall for detecting hamster breeds.

The researchers recommend that future studies broaden the dataset and increase the number of images per class to achieve better results; including other breeds, such as Chinese Hamsters, Turkish Hamsters and more, would further enhance its capability in recognizing other hamster breeds. Additionally, employing more advanced hardware, such as the Raspberry Pi 5 and NVIDIA Jetson, is suggested to achieve noticeable performance improvements. Lastly, future researchers should consider utilizing more advanced architectures than VGG16 to improve efficiency.

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