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Pet Breed Classification and Diet Recommendation Using Deep Learning

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***Abstract*: The rising popularity of domestic pets has generated a new demand for more personalized care systems, especially regarding diet and exercise recommendations based on breed. In this paper, we present a new Pet Care Recommendation System which uses deep learning and advanced image processing techniques to identify pet breeds from images and make breed appropriate recommendations. The model utilizes EfficientNetB5, which provides a high degree of efficiency with 95% classification performance. The accuracy is a result of the design architecture, as well as being trained on a dataset that encompasses a variety of animal breed sets. After breed recognition, the model provides categorized diet plans, which outline recommendations for morning, afternoon, and evening meals per pet breed, along with a recommended walking schedule that fits the individual needs and expectations of a particular breed based on exercise knowledge. The recommendations are made specifically to enhance and/or improve a pet's health and overall well-being. Additionally, the model can be used within a Flask application for real-time user engagement and convenience for pet owners. Through an automated pet identification process and recommendations, the user no longer searches manually, and also saves time while providing scientifically driven findings to enhance a pet's health status. The scalability and flexibility of the application are viable solutions to the demands of the growing pet care industry. Future consideration involves extending the model for multiple types of pets, expanding health monitoring capabilities, and using multiple language options to provide for a broader global client base.**

***Keywords*: Pet Care System, EfficientNetB5, Breed Identification, Flask Application, Diet Recommendations, Walking Schedules, Deep Learning, Personalized Pet Care, Accuracy, Real-Time Recommendations.**

1. Introduction

Looking after pets in urban and suburban settings is becoming increasingly difficult due to busy lifestyles and limited reliable veterinary advice. Thankfully, pets remain an important part of the family unit, which requires precise dietary regimens and exercise for their well-being and health. Pets that are of different breeds must be given differentiated food and exercise so that they can grow properly, develop immunity, and have a satisfactory quality of life. Figuring out these needs and customizing care plans takes a lot of effort, like research, expert meetings etc. We don't have proper information for individual pets, but that can change with modern technology. Since AI and ML have become popular, the pharmaceutical, healthcare, and healthcare sectors have seen development in personalized solutions. This project is a Pet Care Recommendation System that detects pet breeds from images using deep learning and recommends personalized diet and exercise. The system utilizes the EfficientNetB5 model, a highly efficient and accurate convolutional neural network architecture designed for image classification. EfficientNetB5 uses a method called compound scaling, which balances the network's depth, width, and resolution all at once. This helps it deliver high performance while keeping things efficient and less complex. The model identifies the breed of a pet with 95% accuracy, making it perfect for any application in real life, as it has been trained on an extensive dataset of pet images.

This project is innovative because it combines recognizing the specific breed of pet with useful follow-up advice. After recognizing the breed of the pet, the system gives morning, afternoon and dinner customized diet plans. These diet plans are custom-made according to the breed's nutritional requirements [9]. The system also recommends walking timetables by the breeds' energy levels and physical activity needs [10]. For example, longer and frequent walks are recommended for high-energy breeds, while shorter durations are recommended for smaller or less active breeds. Automating these efforts helps the system save time for pet owners besides ensuring proper scientific care practices. To make the system accessible and easy to use, it is implemented as a web application using Flask [12]. Flask is a light-weight yet powerful web framework that enables easy communication between users and the machine learning model [13]. Owners can upload pictures of their pet, and the system will suggest care options in no time [14]. With an easy interface and a speedy response, it is handy for anyone, whether tech-savvy or not. Also, because it is web-based, users can access the system from their home on all devices. This system will tackle the problem of getting tailored pet care solutions for users [15].

It is a system that uses advanced machine learning models as well as a web app to recommend pet care items and food based on information such as the pet's breed and other related details. The technology's capability to pinpoint with great accuracy and provide specific suggestions is what distinguishes it from the other solutions available in the market. The application is

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developed in a modular way so that it can be used in the future as well to include a variety of things such as health monitoring, vaccination reminders, and more compatibility with wearables for pets. The recommendation system for pet care will have an impact on pet care. Also, this technology-based system that's appearing above will help pet owners make choices at ease. Not only does it enhance pet care, but it also enables peace of mind for pet parents to seek support from the app available. With time, this type of advancement will be useful in meeting the varying needs of pet parents. This project shows how deep learning, analyzing images, and understanding users can help make pet care better with technology. The process of this project shows that it is useful, accurate, and stable to use in the real world. The model has a large scope of improvement with proper research and proper use of techniques.

2. Literature Review

The integration of advanced ML and DL techniques in various domains has led to remarkable improvements in accuracy and efficiency. In the below-mentioned sections, we will review various research papers that will explore different methods and models that are applied to specific problems, such as gluten prediction, dog breed classification, animal farming, image classification, and image data augmentation.

IoT System for Gluten Prediction, Jossa-Bastidas et al. [1] have developed a novel IoT-based system for gluten detection in day-to-day flour samples using the NIRS and DL techniques. The system has demonstrated high performance with an XGBoost classifier achieving a high accuracy of 94.52% and a DNN reaching an accuracy of 91.77%. This solution has offered a rapid and low-cost alternative to the traditional gluten detection methods like ELISA and PCR. The study's findings have highlighted the potential of NIRS combined with ML techniques in the food industry, particularly for individuals with gluten-related disorders.

Chinese Native Dog Breed Classification, Zhang et al. [2] have proposed an improved ResNet-based classification method for the Chinese native dog breeds. This model has used ResNet50 as the backbone of the network, achieving an accuracy of 96.4%, surpassing the traditional methods that yielded accuracies of 93.8% and 94.5%. The study applied parallel processing techniques to improve the classification accuracy and has demonstrated how machine learning can be used to preserve and research indigenous dog breeds.

Role of Sensors and Machine Learning techniques in Animal Farming, Neethirajan [3] has explored the use of sensors, big data, and machine learning techniques in modern animal farming. The paper discusses how these technologies can help us reduce production costs, increase it's efficiencies, and improve animal welfare. It also tackles the challenges involved in applying these technologies in real-life farming situations. With the help of sensors and AI, farmers can make smarter decisions that boost both efficiency and sustainable practices in livestock management.

Explainable AI in Image Classification Gorokhovatskyi et al. [4] have focused on improving the interpretability of the CNN-based image classifiers. The author introduces a perturbation-based technique that progressively conceals certain regions within an image to interpret how a neural network arrives at its predictions. This method reveals which image areas are most influential in shaping the model's output, offering greater insight and clarity into otherwise black-box systems. Such interpretability is crucial in sensitive fields like medical diagnostics and security.

Yang et al. [5] conducted a comprehensive review of various image data augmentation methods aimed at boosting deep learning performance in areas like visual recognition, object localization, and scene understanding. By increasing both the variety and volume of training samples, these data expansion strategies help reduce overfitting and improve the model's ability to generalize. The paper also provides a comprehensive taxonomy of methods and discusses the challenges and future directions in this area.

Pet Well-Being and Activity Detection. In the realm of pet care, Hussain et al. [6] have proposed a 1D CNN-based system for the real-time activity detection in dogs. By using wearable sensors such as accelerometers, the model has achieved a high accuracy (99.70% training, 96.85% validation) for recognizing various dog activities like walking, sitting, and eating. This approach demonstrated the feasibility of deep learning in monitoring pet health and behavior continuously. This work underlines the importance of sensor-based solutions for ensuring the pet's well-being.

Wildlife Detection Rithvik et al. [8] introduced a deep learning-based wildlife detection system using CNNs. The system aimed at preventing the animal-vehicle collisions, and therefore utilized preprocessed greyscale images and bounding box detection to classify animals and as a result provide us real-time warnings. The method incorporated AlexNet and ResNet architectures to enhance the performance of result detection, addressing the issue of increasing human-animal conflict in farming areas.

[9] focused on predicting the live body weight (BW) of the indigenous Indian Black Bengal goat breed using a Recursive Partitioning and Regression Trees (RPART) model. This model outperformed the traditional statistical methods by accurately predicting the BW using morphometric data, especially for the heart girth. This work is crucial for improving the decision-making process in goat farming.

Medical Imaging and Explainability, Medical image analysis, especially in critical domains such as diagnostics, benefits from the integration of Explainable Artificial Intelligence (XAI). Van der Velden et al. [7] reviewed XAI techniques in DL-based medical image analysis, proposing a framework to classify these methods based on anatomical location and their interpretability. The paper highlighted the increasing need for transparent models to enhance trust in the AI-driven medical decisions, emphasizing the application of XAI in the healthcare sector.

Waste Management and Environmental Impact Ouedraogo [10] explored the use of ML for waste sorting in municipal solid waste (MSW) disposal, specifically focusing on CNN algorithms for the classification of waste materials. This work explores the negative effects that existing waste disposal methods—especially landfilling—have on both the environment and public health, and it suggests CNN-based solutions for automated waste segregation. This research underscores the importance of AI in achieving sustainable waste management practices.

[11] Al-Maliki, Shatha (2021)This paper explores the use of an Evolutionary Algorithm (EA), specifically the Cooperative Co-evolution Algorithm (CCEA), for image reconstruction and segmentation tasks in medical imaging, such as Positron Emission Tomography (PET) and MRI. The author compares the Fly Algorithm (a specific CCEA variant) with traditional optimization techniques like RCGA, PSO, and CMA-ES for reconstructing PET images. It also discusses the use of interactive data exploration techniques in MRI segmentation of peas within the human stomach.

[12] Zhou, J. (2024). This paper discusses a deep learning-based food image recognition system designed to improve checkout efficiency in university cafeterias. The system uses CNN and FCN to classify food items from images. The study highlights the implementation of data augmentation, regularization, and Dropout techniques to enhance model generalization. Experimental results show an accuracy of 86.88% with stable performance, emphasizing the system's practical applications in food classification.

[13] Chakraborty, Anirban Debabrata, and Pravin Jaronde (2024). This case study centers around building a deep neural network aimed at identifying different dog breeds. The authors explored the application of transfer learning combined with data enhancement strategies, utilizing models such as VGG16 and ResNet50V2. They discuss challenges in classifying different dog breeds and provide insights into real-world applications, such as veterinary and animal services, while improving the deep learning model's performance.

[14] Ye, J., Huang, Z., Wang, Y., & Chen, J. (2023) This paper investigates the use of the HERBS (High-temperature Refinement and Background Suppression) method for fine-grained classification of dog breeds. It outlines the integration of HERBS into various backbone networks for improved breed classification accuracy. The authors demonstrate the model's superior performance compared to other classification methods, showcasing its effectiveness in the dog breed classification task.

[15] Towpunwong, Nattakan, and Napa Sae-Bae (2023). This research aims to classify dog breeds using Convolutional Neural Networks (CNN), specifically focusing on both Thai and foreign dog breeds. The authors use a dataset of 20,949 images and compare six CNN models (Xception, VGG16, ResNet50, InceptionV3, MobileNetV2, and NasNetLarge) for breed classification. The study also covers dog recognition using facial images and assesses how data enhancement methods influence model performance. It achieved impressive results, with breed classification reaching up to 93% accuracy using NasNetLarge, and dog identification hitting 77% accuracy with MobileNetV2.

3. Proposed Methodology

This system implements a pet recognition and recommendation system using deep learning. Based on the pet image classification, the system provides recommendations for the breed along with a diet plan and walk schedule. The method uses a multi-phase approach that involves data collection and cleaning, system building and upgrading, performance testing, and finally, implementation.

1) *Data Collection and Preprocessing*: The images in the datasets are pet images, which are tagged according to different breeds. To maintain uniformity across the dataset, all images are resized to 224×224 pixels. They are then modified through various transformations such as rotation, scaling, resizing, and flipping to enhance the model's ability to generalize. All these changes make the examples a bit different from each other, and it helps the model to learn better. We've split the images into three groups - Learning, Fine-tuning, and Final Assessment. A technique is used to handle the huge dataset efficiently while modifications are made on the pixel values to improve the model's training.
2) *Model Development*: The EfficientNetB5 pre-trained model architecture is chosen and fine-tuned for pet breeds recognition. Initially, the pre-trained layers are kept frozen, and additional dense layers are integrated to classify pet breeds based on the features extracted from the dataset. To enhance generalization and reduce overfitting, BatchNormalization and Dropout layers are applied. Since the task involves multiple classes, categorical cross-entropy is used as the loss function.
3) *Training Process*: The Adamax optimization procedure refines the system with a learning rate of .001. The process tracks correctness and error rate, with evaluation on a separate validation set. This involved several iterations of data augmentation and changes in batch size.
4) *Performance Assessment*: The system is assessed for effectiveness by correctness rates, error analysis, and a classification matrix. Such a classification matrix assists in identifying incorrect identifications and highlights possible insights about specific identifying categories in which the system is struggling.
5) *Recommendation System*: Once the pet breed is classified, breed-specific diet plans and walk schedules are recommended based on predefined rules. For example, if the model predicts a breed like a Labrador, the system suggests an appropriate diet plan and exercise routine tailored to that breed's needs.
6) *Deployment*: The trained model is stored in .h5 format and embedded into a Flask-based web application. This app allows users to provide pet images and receive breed predictions, along with personalized suggestions for their diet and walking routines.

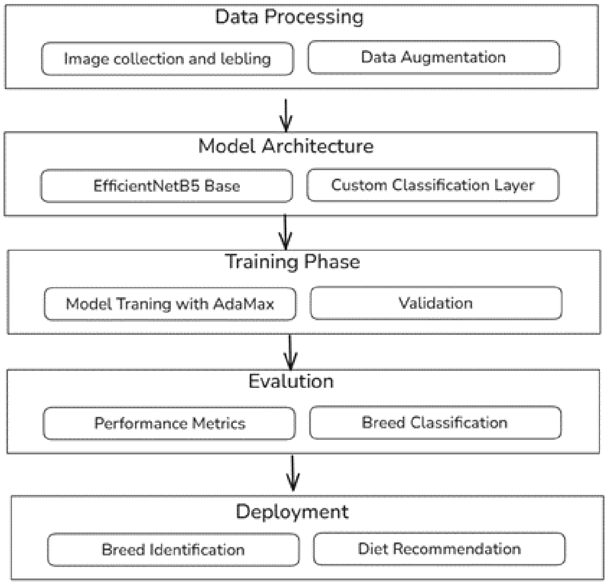

Fig. 1. Flow chart of the proposed methodology

Explanation of the flowchart:

1) *Data Collection*: The first step involves gathering the labelled pet images, which are then preprocessed by resizing them into a uniform dimension and normalizing the pixel values. The dataset is subsequently divided into three subsets.
2) *Data Augmentation*: The dataset is augmented to artificially increase its size and diversity. Training images are enhanced using techniques such as rotation, zooming, and shifting, which help the model perform better on unseen data.
3) *Model Development*: In this step, we define the deep learning models using the EfficientNetB5 as the base. The model is then extended with custom layers, such as a dense layer for classification. At the start, the pre-trained layers are kept frozen, and BatchNormalization along with Dropout layers are introduced to boost the model's performance.
4) *Model Training*: The model is developed using the training dataset and its performance is assessed with the validation set. The Adamax optimizer is employed, and the process is monitored by tracking accuracy and loss over time.

4. Result

A confusion matrix is used to examine the model's effectiveness, offering a detailed view of how accurately it distinguishes between different breeds. Additionally, accuracy and loss curves are plotted to offer a more detailed evaluation of its learning progress and overall effectiveness.

From Figure 2, It can be seen that classification of the model is very clean. Each class is classified clearly as there are less number of misclassification.

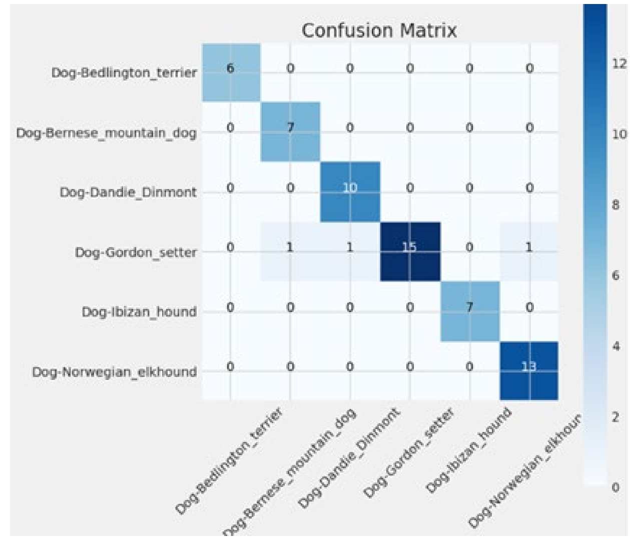

Fig. 2. Confusion matrix

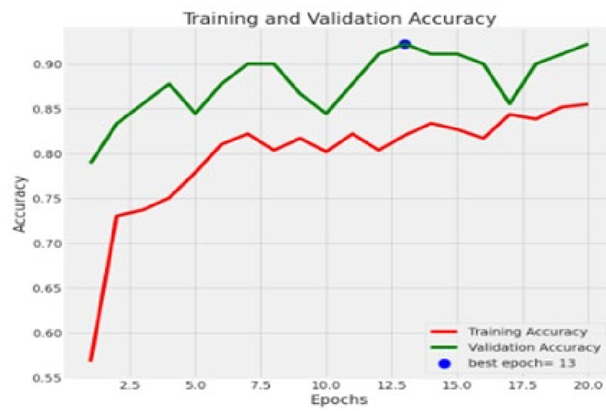

Fig. 3. Epoch vs Training graph for proposed model

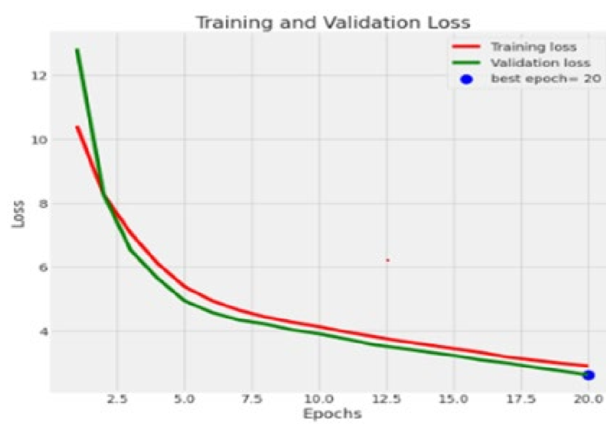

Fig. 4. Epoch vs Loss graph for the proposed model

Figures 3 and 4 illustrate the model's learning progress using two visual plots: the graph on the left displays the training and validation loss, while the one on the right shows the training and validation accuracy. In the loss graph, the red line represents the training loss, which steadily declines over the epochs—reflecting the model's ongoing learning. The green

Table 1
Classification report of proposed model

Class	Precision	Recall	F1- Score	Support
Bedlington_terrier	1	1	1	6
Bernese_ mountain_dog	0.88	1	0.93	7
Dandie_Dinmont	0.91	1	0.95	10
Gordon_setter	1	0.83	0.91	18
Ibizan_ hound	1	1	1	7
Norwegian_elkhound	0.93	1	0.96	12
Accuracy			0.95	61
Macro avg.	0.95	0.97	0.96	61
Weighted avg.	0.96	0.95	0.95	61

line, representing validation loss, also trends downward with minor fluctuations, indicating the model's ability to adjust well to new, unseen data. A blue marker highlights epoch 20 as the point where validation loss is at its lowest, indicating optimal generalization. In the accuracy graph, the red line—indicating training accuracy—shows a steady upward trend, reflecting continuous improvement in the model's predictions on training data. The green line, which represents validation accuracy, also increases at first but shows some fluctuations in the later epochs, with the highest accuracy observed at epoch 13. These visual trends suggest that the model is learning effectively from the training data while achieving its peak performance on unseen data at certain points during training. After these optimal points, chances of overfitting may arise, where training performance continues to improve while the validation performance deteriorates.

Table 1 provides a detailed assessment of the pet recognition model's effectiveness across six distinct dog breeds. Achieving an overall accuracy of 95%, the model demonstrates strong capability in correctly categorizing pet images into their respective classes. Notably, the precision, recall, and F1-scores for the individual breeds highlight their reliability, with the "Dog-Bedlington_terrier" and "Dog-Ibizan_hound" achieving almost perfect scores across all other metrics, indicating their flawless identification. Similarly, breeds like the "Dog-Norwegian_elkhound" and "Dog-Dandie_Dinmont" demonstrate their exceptional performance, maintaining it's F1-scores above 0.95, which signifies both high precision and recall.

However, a minor limitation is observed for the "Dog-Gordon_setter " breed, where the recall is slightly lower at 0.83, indicating to us that a few instances of this breed have been misclassified. The detection rate for this particular breed may be lower due to the presence of some visually similar breeds in the dataset and the limited examples of the "Dog-Gordon Setter" breed. However, the model maintains a strong overall balance across all other classes, achieving a macro-level F1-score of 0.96 and a weighted F1-score of 0.95. Additionally, it generalizes the predictions well beyond the training data without favoring specific breeds.

The results also validate the robustness and reliability of the model in distinguishing between multiple pet breeds, which is therefore critical for applications where the accurate breed identification forms the foundation for subsequent recommendations. The model's strong performance has suggested its suitability for deployment in real-world scenarios, enabling it to deliver some good tailored diet plans and activity schedules based on the identified breed. Furthermore, the consistent metrics across most breeds emphasize the efficiency of the demonstrating its capability to learn intricate breed-specific features from image data.

i. *Recommendation System*: After the model classifies a pet breed, it generates recommendations for diet and exercise specific to the breed. This helps provide personalized care for pets.
ii. *Deployment*: The finalized model is stored in .h5 format and incorporated into a Flask-based application. Users can upload pet images to the Flask app, which uses the model to classify the pet and provide tailored recommendations.

Figure 5 is the deployed Flask application, which is ready for prediction and recommendation.

5. Conclusion

This study put forth a novel Pet Care Recommendation System that utilizes deep learning, coupled with practical care solutions. By taking advantage of the model EfficientNetB5, the system achieves a high breed detection accuracy of 95%, which shows the efficacy of modern neural networks in grouping images. Owners can easily take care of their furry friends with the implementation of feeding and exercising instructions based on the breed type. The care routines also ensure that the pet is healthy. The system's efficiency as a web app based on Flask deployment opens it for wider access and usability improvements as it comes with machine-learning abilities in easy-to-use forms. A pet care recommendation system can have a wide range of uses. From a household with limited space to an animal health centre, the system covers a lot of ground with its real-time feedback and tailor-made care plans. Besides being a great recommendation system, it can also be expanded in the future for a health monitoring system, a behaviour analysis system, and a wearable device integration system. The project not only limits itself to the technology, but also focuses on closing the gaps left by the pet care practices. A lot of the time, they provide generalized advice that does not consider the variety of needs of various breeds. By providing advice based on breeds, this system solves this problem and helps owners of pets live a better life. Pet Care Recommendation System is an excellent project that will cover multiple species and bring in features like health trend prediction and live tracking. In addition, working with animal healthcare professionals will enhance insights and ensure compliance with industry best practices. In conclusion, the Pet Care Recommendation System highlights how AI and machine learning can be leveraged to create meaningful solutions, even within niche domains. The system addresses the specific needs of pet care to provide a personalized touch in a highly intricate area. This project is likely to take care of your pets and their needs in the future as it is accurate, scalable, and holds real-world value.

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