# An Intelligent Approach to Identify Household Canine Dermatology

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***Abstract*—Skin diseases in pets are a prevalent concern, affecting up to 75% of their health conditions. Traditional diagnosis methods for these conditions can be challenging, costly, and time- consuming. Given the increasing use of technology in veterinary medicine, past researchers have explored deep learning methods as a potential solution to improve the diagnosis and treatmentof skin diseases in pets. This study aims to create an intelligent system for pet owners and veterinarians to simplify skin disease identification. The system combines a lightweight deep learning model using a Convolutional Neural Network (CNN) for image analysis with a question-based feature extraction algorithm based on expert consensus. It captures and processes skin disease images, generating predicted scores. These scores are combined with answers to six questions using a weighted scoring algorithm to make the final prediction. The system accurately identifies common pet skin diseases like ringworm, mange, dandruff, and yeast infection with a 93%–98% accuracy rate. Its benefits include saving time and money, ensuring pet health, and pro- viding timely and accurate diagnoses. This technology offers a lightweight, cost-effective, and efficient solution to the challenges of traditional diagnostic methods, promising improved pet care.**

***Keywords*—Artificial intelligence, deep learning, image processing, CNN, canine dermatitis**

## I. Introduction

### A. Overview

The skin is the body's largest and most visible organ and the anatomical and physiological barrier between the animal and the environment. It grants protection from physical, chemical, and microbiological injury, and its sensory components sense heat, cold, pain, itch, touch, and pressure. In addition, the skin is integrated with internal organ systems, thereby reflecting disease processes that are primary or shared with other tissues elsewhere. Skin diseases are one of the most common health concerns among animals, resulting in a weakened immune system once infected. Several clinical reviews have indicated that skin disorders make up a large proportion of small animal patients. It has been estimated that from 20.00% to 75.00% of the cases seen in the average small pet have skin problems as a chief or concurrent owner complaint [1]. In this study, we analyze dermatological diseases associated with dogs because of their close relationship with their owners and the ready availability of data for analysis. Various types of skin diseases common among dogs can be classified as curable and incurable.

Among the curable ones, diseases such as dandruff, yeast infection, allergic dermatitis, and ringworm are often encountered on the epidermal layer of dogs' skin [2]. This study aims to develop a skin disease identification deep learning model with domain knowledge-based weighted scoring algorithms for household dogs. The proposed intelligent system intends to cater to innovations in dermatology diagnostic procedures to meet animals' physical and mental well-being, which are growing global concerns. Through this study, we can predict the disease based on a clear image of the dog's skin disease and some additional information from the dog owner. The proposed deep learning model and the algorithm will extract the features of the image given as input and identify if it belongs to one of the diseases mentioned above. In the end, accuracy and severity will be providedconsidering the output of the process diagnosis.

### B. Background and Significance

The health of animals, whether livestock or pets, is inextricably linked to the well-being of people and the planet, meaning better animal health plays an integral role in sustainability. Surveys conducted in many countries show thatthe population of dogs as pets is increasing rapidly [3, 4]. Parallel to this increase in the dog population, the various diseases associated with them spread swiftly. Studies [5] and [6] show that skin diseases are prominent among them. When a pet gets sick or shows abnormal behavior, normally the owner is required to visit clinics and contact a doctor. There are no other options because of the knowledge gap and difficulties in understanding. Considering the above factors, veterinary doc- tors get a significant percentage of daily skin disease cases [7]. Pet owners have to spend high costs here, and pets take longer to recover. Even doctors may find distinguishing diseases with similar clinical signs challenging through a general test. As a result, one has to resort to advanced tests to differentiate the diseases, which takes time and can be inaccurate. A solution to the points mentioned above is an intelligent algorithm to identify and predict the health issues of our pets and animals via visual inspection and data analysis. This solution lets the pet owner diagnose their dog's skin diseases without visiting the clinic and saves unnecessary expenses. Not only pet owners but also doctors can use this intelligent system to confirm their judgment in some cases. To validate the claims of this study, Table I provides a comprehensive comparison between diseases based on the identified features. All these identified features are based on the knowledge of veterinary domain experts and previous studies [8, 9, 10, 11].

TABLE I
DISEASE COMPARISON

| Disease Appearance | Disease | | | |
|---|---|---|---|---|
| | *Dandruff* | *Mange* | *Ringworm* | *Yeast infection* |
| Itchiness | ✓ | ✓ | ✓ | ✓ |
| Thickened<br>Drie oily and greasy infected area | | | | ✓ |
| A musty odor | ✓ | | | ✓ |
| Notice white flakes | ✓ | | | |
| Redness with roughlyred ring appearance | | | ✓ | |
| Red ring appearance<br>Patches of hair loss and crusting | | ✓ | | |

### *C. Related Works*

Skin diseases are a common concern for pet dogs; early detection is vital for their well-being. Traditionally, veterinarians visually assess these conditions, which can be time- consuming and subjective. However, recent advances in deep learning and computer vision have spurred interest in creating intelligent systems to identify dog skin diseases accurately through images. In 2017, a research team proposed using deep learning to categorize dog skin diseases using multispectral imaging. They aimed to distinguish between bacterial dermatosis, fungal infection, and hypersensitivity allergic dermatosis. They gathered regular and multispectral images to build their model and employed four CNN model architectures: Inception, ResNet, DenseNet, and MobileNet. These models were trained on data from 15 species of 94 dogs, with data augmentationto enhance accuracy. The study reported moderate accuracy levels and Matthews Correlation Coefficients (MCCs) for eachdisease on the validation dataset. However, the researchers recommended incorporating a consensus approach to improve model performance. Subsequently, the same study showed that consensus models outperformed individual models, achieving higher accuracy and MCCs for each disease on the validation dataset [12]. In 2018, another study introduced an intelligent dog skin disease detection system, incorporating ontology- based clinical information extraction. This mobile application integrates disease identification, severity detection, domain- specific knowledge, and an AI-based chatbot for dog owners. It enhances its functionality by utilizing CNNs and Natural Language Processing (NLP) techniques. The researchers collected and processed images of ringworm, dandruff, and yeast infection, employing augmentation to expand the dataset. Several models were tested, with a model featuring a convolutional layer in a 2D pattern outperforming transfer learning with 98% accuracy. The study's future focus is expanding the system's capability to categorize additional skin conditions and assess severity levels using images and text data [13]. In 2019, researchers concentrated on three dog skin diseases: mange, ringworm, and fleas, using color pictures from clinical and online sources. They applied a CNN with three layers featuring 16, 32, and 64 output channels. The algorithm was trained on a dataset split into a training and validation set, and it generated images with skin disease labels. The model achieved a training accuracy of 82%, a validation accuracy of 55%, and a loss of 46% [14].

## II. METHODOLOGY

Over the past few years, the use of deep learning techniques for detecting skin diseases in household dogs has grown substantially. The current study aims to contribute to this emerging field by developing a lightweight, intelligent system that combines deep learning models and domain knowledge algorithms. This system can accurately classify and identify various skin conditions in dogs while also being able to deploy on mobile platforms. To achieve this, the study followed a comprehensive methodology that included collecting and preprocessing data, designing the architecture, training the model, and evaluating its performance.

Integrating domain knowledge algorithms into the deep learning model helps to develop an intelligent system that offers an accurate and reliable diagnosis of skin conditions in dogs to veterinary professionals and pet owners. This can enhance the health and well-being of household dogs by making the diagnosis and treatment of skin diseases more efficient and effective. The proposed intelligent system is focused on detecting four skin diseases commonly found in dogs: ringworm, dandruff, yeast infection, and mange.

Identifying skin diseases in dogs in this study involves two critical steps. First, the user uploads an image of the infected area. Second, the user responds to a series of simple yes or no questions presented by the intelligent system. Using deep learning models and domain knowledge algorithms, the system analyzes the user's responses and the uploaded image to determine and communicate the specific skin disease afflicting the dog. This method provides an efficient and user-friendly approach to identifying common skin diseases in household dogs, which could enhance accuracy and speed of diagnosis.

### *A. Data Collection*

To collect data for this study, a comprehensive approach was employed that involved collecting images of infected areas from various sources, including veterinary clinics such as Welisara Veterinary Hospital, Sri Lanka, and Peradeniya Veterinary Teaching Hospital, Sri Lanka, as well as past research papers [13]. Related information about each image, such as the type of skin disease and any relevant medical history, was also obtained from these sources. The collected data were then subjected to thorough quality checks and preprocessing to ensure its suitability for the deep learning model. Overall, this rigorous data-gathering process ensured that the resulting model was trained on a robust and diverse dataset capable of accurately identifying various skin diseases in household dogs.

### *B. Development Tools*

As for the development library, TensorFlow was chosen as the primary tool for building and training machine-learning models. As an open-source software library specifically designed for machine learning and deep learning applications, TensorFlow provides a flexible architecture and intuitive Application Programming Interfaces (APIs) for easy designing and training models while optimizing performance. Tensor- Flow's capacity to handle large datasets and scale models across multiple devices made it an obvious choice to implement the proposed algorithm.

### C. Data Preprocessing

Identifying skin diseases from images entails several critical steps. The initial step involves accurately labeling the dataset, ensuring correct categorization for each distinct skin condition. This precise labeling is fundamental to training a dependable system. Following this, the images undergo preprocessing procedures, including techniques such as Laplacian sharpening, Gaussian smoothing, Sobel operator and Canny edge detection. Notably, the study revealed that using the following specific kernel 1 for image sharpening produced the most favorable outcomes regarding accuracy and effectiveness.

$$Kernel = np.array([[0, -1, 0] \\ [-1, 5, -1], \\ [0, -1, 0]]) \tag{1}$$

A common challenge is having an insufficient number of images for each disease. Data augmentation techniques, including rotation and flipping, were used to expand the dataset to a minimum of 250 images for each condition. Datasets are typically split into three parts: 70% for training, 20% for validation, and 10% for testing. This ensures practical model training, validation, and testing to assess performance without overfitting.

### D. Proposed Algorithm

1) Skin disease classification model

This research aimed to create a mobile-friendly, lightweight expert system that utilizes deep learning models to classify disorders accurately. We employed five different CNN models and transfer learning approaches to categorize images into four classes to achieve this goal. We utilized different CNN architectures with varying layers to make it easier to select the best-performing lightweight model during the final implementation of the expert system. This approach improved the comparison of results and ultimately led to a more accurate disorder classification.

a) Vgg16
b) MobilenetV2
c) Squeezenet
d) Efficientnet
e) Cmax8net (CNN 2-dimensional pattern)

Vgg16, Efficientnet, Squeezenet, and Mobilenet are examples of lightweight transfer learning models that have been pre-trained on large datasets. In contrast, the 2-dimensional CNN model (cmax8net) used in this research was developed specifically for this study. The architecture of the proposed Cmax8net CNN model is presented in Fig1 the model has several layers, including four

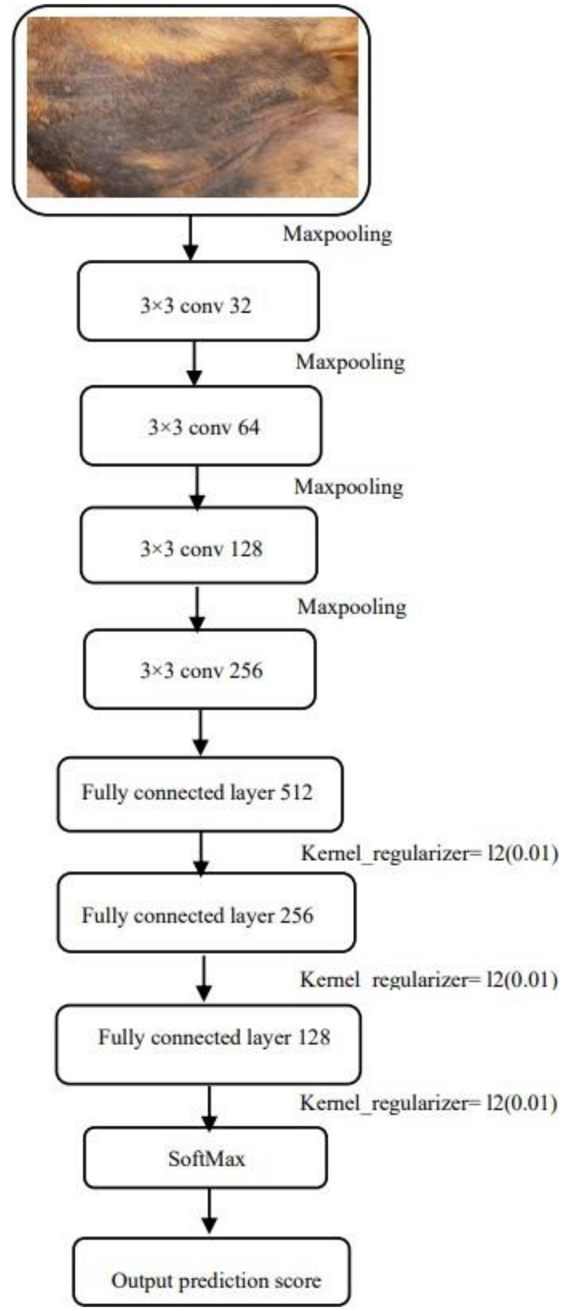


Fig. 1. Architecture of Cmax8net model.

convolutional layers, four max-pooling layers, and four dense layers. The first layer is a 2D convolutional layer with 32 filters, a filter size 3x3, and a rectified linear unit (ReLU) activation function. The input shape is specified as an argument in this layer. The second layer is a max-pooling layer with a pool size of 2x2. The following three convolutional layers have 64, 128, and 256 filters, respectively, with the same filter size and activation function as the first layer. Each convolutional layer is followed by a max-pooling layer with the same pool size. The fully connected layers consist of a flattened layer and three dense layers with 512, 256, and 128 units, respectively, and a ReLU activation function. The regularization technique l2 regularization is applied to the second, third, and fourth dense layers with a regularization rate of 0.01. Finally, the last dense layer has four units and a SoftMax activation function to output the predicted probabilities of the input belonging to one of the four classes.

2) Weighted scoring algorithm

Identifying the presence of a disease in a dog requires a comprehensive diagnostic process that considers various factors, including the animal's external physical characteristics. To this end, a domain knowledge" weighted scoring algorithm" has been devised that relies on responses to six straightforward questions about the dog's physical attributes. The weighting of each question in the algorithm was generated based on input from veterinary professionals and internet sources, specifically regarding the questions' relevance to identifying the disease in question.

- A weight of 0.5 was assigned to questions that directly impact the diagnosis of the illness.
- While those that influence the diagnosis to a certain extent were given a weight of 0.2.
- The remaining questions were assigned a weight of 0.03.
- Respondents were provided with three response options:" a lot,"" a little," and" not at all," each of which was assigned a score of 1, 0.5, and 0, respectively.

Accordingly, the questions are as follows:

I Does your pet frequently itch from the infected area?
II Does the skin in the infected area look oily, greasy, thickened, and scaling?
III Do you feel a musty odor or a strange odor from the infected area?
IV Do you notice white flakes in the infected area?
V Are there any lesions that look roughly like a red ring?
VI Can you see patches of hair loss with scaling and crusting skin?

The weights given based on the domain knowledge for each question for each disease are shown in the following Tab. 2. Thus, a predicted score for each disease, the values associated with the responses provided by the respondent, are multiplied by the weights assigned to each question in the domain knowledge algorithm. The resulting products are summed to produce a domain knowledge predicted score for each disease. This process allows for a quantitative assessment of the likelihood of a particular disease based on the external characteristics of the dog, providing valuable insights to inform the diagnostic process. By leveraging the expertise of veterinary professionals and domain experts in developing this algorithm, the resulting predicted scores are more accurate and reliable, enhancing the quality of disease diagnosis in dogs. The predicted scores of a deep learning model and a domain knowledge algorithm are combined to enhance the accuracy of disease diagnosis in dogs. Specifically, the scores predicted by each method are weighted equally, with each contributing 50% to the final disease prediction. The disease with the highest predicted score, as determined by the combined scores from the deep learning model and domain knowledge algorithm, is ultimately considered the final diagnosis. This approach represents a valuable advancement in disease diagnosis, as it leverages the power of machine learning and the insights of domain experts to produce a more accurate and reliable prediction. Finally, when summarizing the methodology, the inputs and outcomes of each stage can be represented in a flow chart, referred to as Fig 2

TABLE II
WEIGHTS FOR EACH DISEASE

| Skin Disease | Questions | | | | | |
|---|---|---|---|---|---|---|
| | QI | QII | QIII | QIV | QV | QVI |
| Ringworm | 0.2 | 0.03 | 0.03 | 0.03 | 0.5 | 0.2 |
| Mange | 0.2 | 0.03 | 0.03 | 0.2 | 0.03 | 0.5 |
| Dandruff | 0.2 | 0.03 | 0.2 | 0.5 | 0.03 | 0.03 |
| Yeast infection | 0.2 | 0.5 | 0.2 | 0.03 | 0.03 | 0.03 |

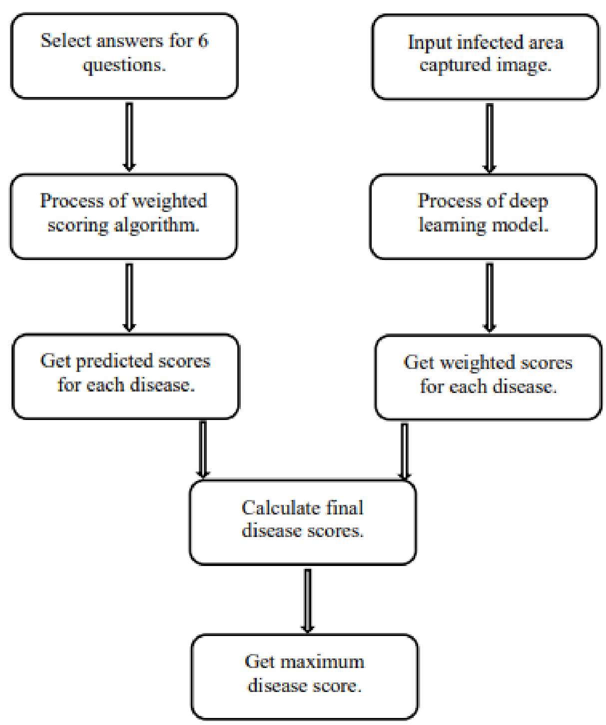


Fig. 2. Conceptual framework of the expert system

## III. Results and Discussion

The study aims to develop a dog skin disease identification system using machine learning and domain knowledge-based weighted scoring algorithms. The primary objective is to create a lightweight, mobile-friendly system that assists veterinary professionals and pet owners in identifying four common skin diseases in dogs: ringworm, mange, dandruff, and yeast infection. The data collection process involves compiling a dataset of images and related information for each disease, which is then utilized to train and test the machine learning model. The weighted scoring algorithm is developed based on six questions and their relative importance for each disease. In this results section, we present the accuracy results obtained from both the machine learning model and the weighted scoring algorithm, as well as the final prediction and weight distribution used in the system.

### *A. Skin disease identification using infected images*

The main objective of this study is to develop lightweight, mobile-friendly deep-learning models for skin disease identification utilizing CNNs. The study assesses transfer learning models, including Vgg16, Efficientnet, mobilenetv2, Squeezenet, previous study custom model [14], and a proposed model (cmax8net) based on the conv2d architecture. After augmenting the dataset, each model is trained using approximately 250 images per disease. The testing accuracy obtained for eachmodel is recorded and presented in Tab. 3.

TABLE III
Accuracy Table

| Model | Accuracies |
|---|---|
| Custom model [14] | 0.4700 |
| Squeezenet | 0.5600 |
| Mobilenetv2 | 0.8515 |
| Vgg16 | 0.9348 |
| Efficientnet | 0.9672 |
| Cmax8net | 0.9753 |

Analysis of the obtained accuracies presented in the table reveals significant findings. The mentioned Squeezenet model and conv2d model, which were proposed in a previous research study [14], yielded unsatisfactory results when trained on the current image dataset, exhibiting notably low accuracy. This suggests that those models may need to be better suited for the specific characteristics and complexities of the given dataset. The lower accuracy obtained highlights the need for careful consideration and evaluation of different models in the context of the dataset to identify the most suitable architecture for achieving better performance. The evaluated models, including Mobilenetv2, Vgg16, Efficient-net, and the proposed CNN model (Cmax8net), demonstrated impressive accuracy rates and were further improved through data augmentation techniques. Mobilenetv2, known for its lightweight and efficient nature, offers a compelling option for applications with limited computational resources. Efficientnet is also renowned for its lightweight nature and ability to achieve impressive accuracy on image classification tasks while maintaining high computational efficiency. It combines advanced scaling techniques with efficient network architecture design to deliver exceptional performance with minimal computational resources. In contrast, vgg16 is often favored in tasks that require high accuracy, such as image classification, object recognition, and fine-grained visual tasks. However, in terms of being lightweight and suitable for mobile platforms, the proposed model emerged as the frontrunner, offering a balance of accuracy and efficiency. Notably, the proposed cmax8net model's architecture is less complex than the other transfer learning models discussed, yet it achieves accurate predictions. The accuracy, which is further improved through data augmentation, could be refined by hyperparameter tuning. Specifically, a batch size of 128, 20 epochs, and a learning rate 0.0001 are selected as the hyperparameters. During training, the model exhibited significant progress, with the validation accuracy initially at 0.39 and gradually increasing to 0.98 after 20 epochs. Similarly, the validation loss shows a notable reduction from its initial high value to 4.456. The model's performance on the test data yields an accuracy of 0.9753 and a loss of 4.3080. When evaluated with external data, the model consistently produces highly accurate predictions, achieving testing accuracies ranging between 90% and 100% for each disease class.

In Fig 3, a confusion matrix is presented, which is a table displaying the counts of true positives, true negatives, false positives, and false negatives. This table is used to evaluate the performance of a classification model. In Fig 4, the accuracy graph of the Cmax8Net model is shown. This graph illustrates the model's accuracy.

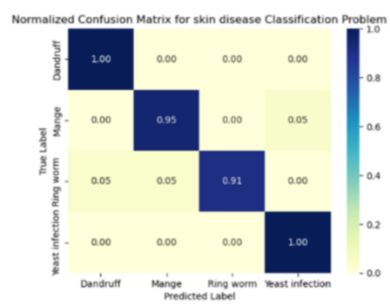


Fig. 3. Confusion matrix

### *B. Skin Disease Identification Using Weighted Scoring Algorithm*

A scoring system has been developed to evaluate responses to six disease-related questions, taking into account weights and probabilities determined by experts and online sources. To determine the effectiveness of this system, a survey was conducted among 30 veterinary school students to assess its accuracy. The aim of the survey was to compare the students' answers to the established standards. The results for each disease are presented in Fig 5, Fig 6, Fig 7, and Fig 8.

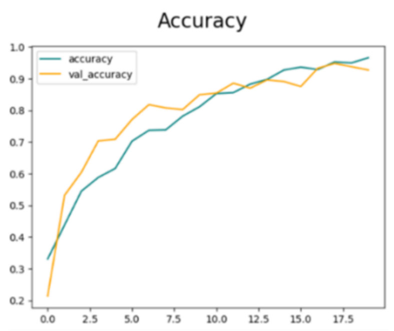


Fig. 4. Accuracy graph

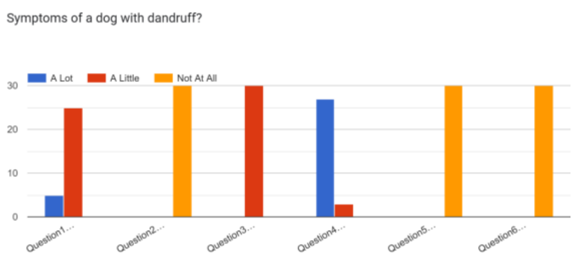


Fig. 5. Survey results in Dandruff

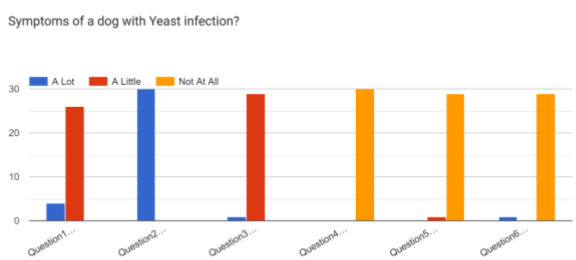


Fig. 6. Survey results in Yeast infection

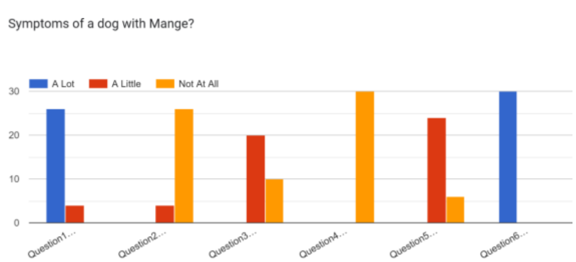


Fig. 7. Survey results in Mange

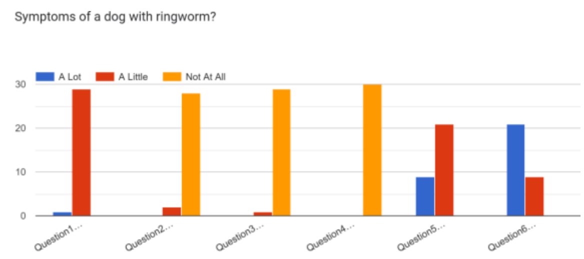


Fig. 8. Survey results in Ringworm

Based on the above graphs, the selected answers for each disease are calculated as a percentage and presented in Tab. 4, Tab. 5, Tab. 6, and Tab. 7.

TABLE IV
DANDRUFF AS A PERCENTAGE

| Question | A lot (%) | A little (%) | Not at all (%) |
|---|---|---|---|
| I | 16.6 | 83.4 | - |
| II | - | - | 100 |
| III | - | 100 | - |
| IV | 90 | 10 | - |
| V | - | - | 100 |
| VI | - | - | 100 |

TABLE V
YEAST INFECTION AS A PERCENTAGE

| Question | A lot (%) | A little (%) | Not at all (%) |
|---|---|---|---|
| I | 13.3 | 86.7 | - |
| II | 100 | - | - |
| III | 3.3 | 96.7 | - |
| IV | - | 1- | 100 |
| V | - | 3.3 | 96.7 |
| VI | 3.3 | - | 96.7 |

TABLE VI
RINGWORM AS A PERCENTAGE

| Question | A lot (%) | A little (%) | Not at all (%) |
|---|---|---|---|
| I | 86.7.3 | 13.3 | - |
| II | - | 13.3 | 86.7 |
| III | - | 66.6 | 33.3 |
| IV | - | 1- | 100 |
| V | - | 80 | 20 |
| VI | 100 | 3- | - |

According to the methodology described earlier, higher percentages are obtained for the" a lot" option in questions deemed crucial for identifying each disease. This implies that selecting" a lot" for a question with a higher weight would result in a higher predicted score for that particular disease, indicating a correct prediction. Consider the example of dandruff: questions regarding the presence of white flakes, frequent rubbing of the affected area, and a strange smell are found to influence its identification significantly. The table

TABLE VII
MANGE AS A PERCENTAGE

| Question | A lot (%) | A little (%) | Not at all (%) |
|---|---|---|---|
| I | 3.3.3 | 96.7 | - |
| II | - | 5.6 | 90.4 |
| III | - | 3.3 | 96.7 |
| IV | - | 1- | 100 |
| V | 30 | 70 | - |
| VI | 70 | 30 | - |

provided in the previous section shows that a very high percentage of respondents selected" a lot" or" a little" for these three questions, while the percentage for" not at all" is 0. Consequently, this algorithm exhibits nearly 100% accuracy in identifying the presence of dandruff. Considering all diseases, the scoring algorithm achieves an accuracy rate close to 100% for each disease. In summary, the weighted scoring algorithm's effectiveness in predicting diseases is assessed based on the percentages of different response options, particularly the higher-weighted questions. In the final prediction process, both the image prediction score and the weighted scoring algorithm contribute equally, each carrying a weight of 50%. This unique characteristic significantly influences the weighted scoring algorithm's overall prediction. Notably, the weighted scoring algorithm consistently achieves a high accuracy rate, often nearing 100%. Consequently, even in cases where the image prediction may result in misclassifications, the weighted scoring algorithm effectively corrects them. In recent studies [13], it is also mentioned that beyond the captured image, it is valuable to make a final prediction based on the behavior and characteristics of the pets. Therefore, that novelty part occupies a special place in this study.

### C. Conclusion and Future Work

Skin diseases in household pets, especially dogs, are a prevalent and concerning issue that can cause various health problems. Unfortunately, conventional diagnosing of these conditions is often burdensome, costly, and time-consuming. Recognizing this challenge, researchers have explored deep learning techniques to improve the accuracy and efficiency of diagnosing and treating skin diseases in pets. This study aims to develop a lightweight and mobile-friendly intelligent system that combines deep learning methods with a weighted scoring algorithm based on domain knowledge. The objective is to provide a simplified approach for identifying skin diseases that is accessible to both pet owners and veterinarians. The proposed intelligent system leverages CNN models and a feature extraction algorithm based on a series of questions to detect skin diseases in pets accurately. The system generates predictive scores by inputting images into the deep learning models. These scores are then combined with the results obtained from answering specific questions using a weighted scoring algorithm. The final prediction is determined by considering the scores derived from both the deep learning models and the weighted scoring algorithm. On mobile platforms, this study's results showcase the system's effectiveness in accurately predicting common skin diseases in pets, including ringworm, mange, dandruff, and yeast infection, with an impressive accuracy range of 93% to 98%. Implementing this mobile-friendly system offers several benefits, such as cost and time savings, improved pet health and well-being, and accurate and timely diagnosis and treatment of skin diseases. This intelligent system presents a promising solution for overcoming the challenges of diagnosing skin diseases in pets by addressing the limitations associated with traditional diagnostic methods. Based on the current study's findings and limitations, several suggestions for future work can be made:

I Expanding the data set by increasing its size, diversity, and quality, collaborating with multiple veterinary clinics, and collecting data from different geographical locations is recommended. This would improve the generalization and accuracy of the deep learning models used for diagnosis.

II The skin diseases the system covers should be expanded beyond the existing four (ringworm, mange, dandruff, and yeast infection) to include more common types found in dogs. Developing a mobile application or device that enables real-time image capture and analysis would facilitate the immediate diagnosis and tracking of skin conditions.

III Collaborating with more veterinarians would provide valuable insights to validate and refine the system and contribute additional labeled data. Creating a user-friendly interface for pet owners and veterinarians, with clear instructions, visual aids, and explanations, is crucial. Regular updates to the deep learning models should be performed to incorporate new data and advancements in the field.

IV Exploring the integration of telemedicine capabilities would enhance accessibility and convenience for remote pet owners.

V User feedback surveys and evaluations should be conducted to improve usability, accuracy, and effectiveness.

Implementing these suggestions would contribute to developing a comprehensive expert system for identifying and diagnosing skin diseases in household pets.

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