Canine Dermal Analyser: Harnessing Artificial Intelligence and Deep Learning to Revolutionize Canine Skin Disease Detection

Thomas Mathew Jose
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
thomasmathewjose2025@cs.ajce.in

Mathew Abraham
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
mathewabraham2025@cs.ajce.in

Sebastian Biju
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
sebastianbiju2025@cs.ajce.in

Samuel Michael
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
samuelmichael2025@cs.ajce.in

Minu Cherian
Dept. of Computer Science
Amal Jyothi College of Engineering (Autonomous)
Kottayam, India
minucherian@amaljyothi.ac.in

Abstract—Skin diseases in dogs are a prevalent concern, requiring timely and accurate diagnosis for effective treatment. This study proposes an intelligent system that integrates a Convolutional Neural Network (CNN) with lesion segmentation and a weighted scoring algorithm to improve classification accuracy in multiple disease categories such as ringworm, mange, and yeast infection. Unlike traditional deep learning approaches, our method incorporates lesion segmentation to isolate affected areas prior to feature extraction, improving the model focus on disease-specific patterns. Additionally, a domain knowledge based weighted scoring algorithm refines predictions by combining CNN-derived probabilities with owner-provided symptom assessments. The methodology involves pre-processing images for noise reduction, lesion segmentation for targeted analysis, CNNbased feature extraction, and a scoring mechanism that weighs expert-defined symptoms. Experimental results demonstrate a classification accuracy of 98%, significantly enhancing reliability compared to conventional CNN-only models. This hybrid approach offers an efficient, cost-effective and mobile-friendly diagnostic tool, empowering both pet owners and veterinarians with rapid and precise skin disease identification, ultimately improving canine care.

Index Terms—Canine skin disease detection, convolutional neural networks (CNNs), image segmentation, veterinary diagnostics, machine learning, lesion detection, computer vision, deep learning, automated disease classification, weighted scoring algorithm

I. INTRODUCTION

Studies show that dermatological illness account for up to 75% of canine veterinary cases, making dermal diseases one of the typical health problems affecting household dogs. In addition to harming dogs, these conditions—which can include everything from fungal diseases like ringworm to parasitic infections like mange—also increase the risk of zoonotic transmission, which can have a negative impact on human health. Veterinary physical examinations and laboratory testing are the traditional diagnosis methods, which are sometimes expensive, time-consuming, and require specialized knowledge. We aim to use technology to diagnose skin problems in dogs early on, ensuring their health and well-being. Traditional diagnostic methods can be slow and need veterinary knowledge, resulting in delays and discomfort. Our solution uses advanced image analysis for fast, reliable detection, allowing pet owners and veterinarians to discover issues early. By combining innovation and compassion, we hope to ease pet health concerns, and improve veterinary care.

With the increasing awareness of pet health, there is an urgent need for a simple and effective method that can help in the detection of skin diseases in dogs, so that treatment can be provided in a timely manner, and with a better prognosis. The proposed system is a mean to overcome this issue, which will ultimately help pet owners and veterinarians to diagnose skin conditions faster and accurately and by doing so provide a trustful tool for early diagnosis. We built a platform that combines state-of-the art technology with human-centered design in order to the wide access to high-quality diagnostic support. Moreover our solution can foster more awareness of pet health in the community and animal welfare through better and early actions.

II. LITERATURE SURVEY

Since the advancements in deep learning and computer vision, you can now detect skin diseases in animals, especially dogs, much earlier than before. These technologies are able to provide persistent and available diagnostic resources that can help both pet owners or veterinarians to identify skin conditions with increased accuracy and speed.

A. Deep Learning for Canine Skin Disease Detection

Convolutional neural networks based machine learning algorithms, in particular, have been widely used in diagnosing skin diseases in pets, providing a cost-effective and accurate alternative to traditional approaches. Hwang et

DOI: ***10.5281/zenodo.15514603***

al. proposed multispectral imaging based deep learning approach for diagnostic accuracy enhancement, and established the feasibility of convolutional neural network (CNN) architectures in differentiating between bacterial, fungal, and allergic skin conditions [1]. Similarly, Thoutam et al. utilizing transfer learning on pre-trained CNNs with InceptionV3, and MobileNetV2, achieved validation accuracy of 98% emphasized the relevance of CNNs on veterinary dermatology [2]. Moreover, Kudahetty et al. combined both application and extraction which is based on knowledge-based weighted scoring algorithm, which integrated into deep learning to improve the dependability of prediction and diagnosis [3]. It allows fast and clear insight into conditions like ringworm, mange, dandruff and yeast infection, and improves actors in pet healthcare.

B. Mobile and AI-Driven Diagnostic Applications

Mellores et al. proposed android based application using Artificial Neural Network (ANN) and OpenCV for real time detection of skin disease [4]. Their system allows dog owners to take and analyze images of their pets' skin to allow for early intervention without an immediate visit to the vet. Also, Rathnayaka et al. have implemented natural language processing (NLP) within a chatbot which assists users to understand the severity of the disease and possible treatment options [5].

C. Image Processing Techniques in Veterinary Dermatology

By leveraging deep learning, combined with image processing techniques like segmentation and feature extraction, diagnostic performance can be enhanced. Sonia et al. employs a fruit fly optimization algorithm to improve segmentation accuracy in skin lesion detection [6]. Their classifier employed an eigenvector-based feature ranking to enhance classification performance. Moreover, Kolli et al. showed how hybrid models combining neural networks with decision trees could predict the time it takes for a wound to heal given images of segmented wounds [7].

D. Additional Studies

With machine learning and image processing, dermatological diagnostics have significantly improved. Jaiyeoba et al. combined together traditional classifiers and deep learning architectures to form a stacking ensemble model which has resulted in 99.30% accuracy for the classification of Erythemato-Squamous Diseases [8]. Smith et al. presented a system based on Tiny YOLOv4, named Pawgnosis, able to detect canine pododermatitis and neoplasia with 0.95 mean average precision [9].

Eliwa et al. suggested a CNN tuned with the Grey Wolf Optimizer for the classification of monkeypox skin lesions, yielding an 95.3% accuracy [10]. Mittal et al. proposed DermCDSM, an improved system for skin disease classification based on Improved Chameleon Swarm Optimization (ICSO) and Deep Spiking Neural Networks (CD-SNN) [11].

Bagheri et al. combined Mask R-CNN, Multi-Atrous Full-CNN (MAFCNN), and geodesic segmentation for enhanced accuracy in lesion boundary refinement [12]. Nguyen et al. improved U-Net architecture with EfficientNetB4 and ResNetbased residual blocks, and perform better segmentation in ISIC dataset [13].

Girma et al. used CNN and SVM to classify Lumpy Skin Disease, attaining 95.7% accuracy [14]. Saroja et al. used YOLOv8 nano for the detection of pet skin disease in real time [15].

E. Future Directions and Challenges

While these models have shown great potential, there are still many challenges related to limited datasets, diversity in skin conditions, and the demand for real-time processing in dermatological applications that require further investigation. Further advancements in training datasets, enhancements to mobile AI applications, and incorporating multiple data modalities (thermal imaging, spectral analytics, etc.), will enhance diagnostic accuracy and accessibility in veterinary medicine.

Through the integration of AI, mobile applications, and advanced image processing techniques, contemporary veterinary diagnostics are stepping toward efficient, elevated, and user friendly solutions that put animal health first.

III. METHODOLOGY

A. System Architecture

The system architecture of Canine Dermal Analyser shown in Fig. 1 leverages a Convolutional Neural Network (CNN) combined with lesion segmentation and a weighted scoring algorithm for canine skin disease classification. The architecture comprises two primary pathways: image-based analysis and user-reported symptoms.

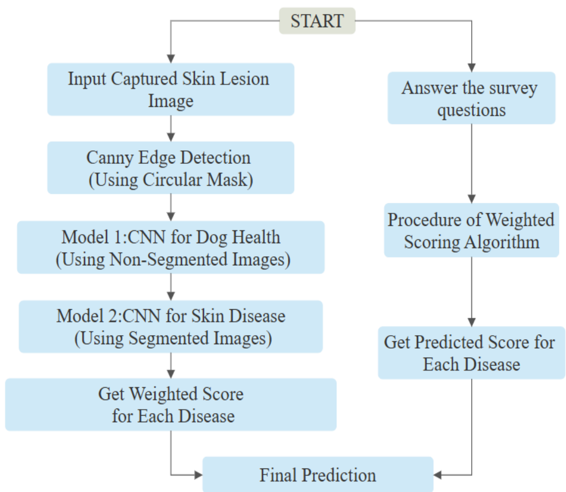

Fig. 1. System Architecture

The skin lesion image is first acquired, and edges of the lesion are detected using Canny edge detection with a circular mask on the image processing pipeline. The first CNN model assesses overall dog health status based on the non-segmented images, whereas the other CNN model analyzes disease classification using the segmented images of the lesions. At the same time, the system collects user-reported symptoms via survey and runs them through a weighted scoring algorithm. These scores are combined to produce the final classification of the disease. By combining visual and contextual data, this hybrid method increases reliability and offers an efficient, accessible diagnostic platform for pet owners and veterinarians.

B. Dataset

For this project, we collected dataset from various online databases, as well as a local veterinary clinic, with images of canine skin diseases. We validated each image to ensure quality and relevance. Noise reduction, contrast adjustment, and conversion to HSV color space are part of preprocessing steps for precise identification of the lesion. Next, a segmentation mask was applied to segment the area of interest, which was followed by morphological operations to remove noise. Lesion contours were extracted and Contrast Limited Adaptive Histogram Equalization (CLAHE) improved the visualization. Such refined images were used to train the CNN model that could classify mange and ringworm with high accuracy, thus aiding diagnostics.

C. Technologies Used

Canny Edge Detection and Inception V3 is used to improve image processing and classification accuracy. Canny Edge Detection with OpenCV detects edges by looking for sudden intensity changes. It is processing based in multiple-stages which starts with noise-reduction with Gaussian filter then moves to gradient computation, non-maximum suppression and then hysteresis edge tracking. This helps in precise segmentation of lesion to classify better. Inception V3, an advanced Inception architecture, using factorized convolutions, batch normalization and auxiliary classifiers gives better performance. Its multi-path architecture effectively captures spatial features and classifies canine skin diseases with high accuracy in an efficient manner.

D. Proposed Algorithm

1) Disease classification CNN-model: The disease detection phase utilizes advanced Convolutional Neural Networks (CNNs) to classify canine skin diseases with high accuracy as shown in Fig. 2. The model is based on Inception V3, which is a deep learning architecture that captures detailed information through several layers. The refined images obtained from the segmentation process serve as inputs, ensuring that the model focuses specifically on affected skin regions.

The architecture begins with feature extraction using Inception V3, where high-level features are derived from input images. These features are then flattened to convert three dimensional feature maps into a one-dimensional vector, allowing for efficient processing in the subsequent layers. A dense layer with 512 neurons and a ReLU activation function is incorporated to introduce non-linearity and improve learning capabilities. To prevent overfitting, a dropout layer with a 50% dropout rate is applied, deactivating half of the neurons randomly during training. The final layer consists of a single neuron with a sigmoid activation function, outputting probabilities indicating the presence of the disease.

The Adam optimizer and binary cross-entropy loss are used for compilation of the model. The final output is a binary classification of whether the dog has mange or ringworm which helps in timely diagnosis and helps the veterinary professionals in a better decision making.

2) Weighted Scoring Algorithm: A weighted scoring algorithm, developed by veterinary experts and online sources improves the diagnosis of canine diseases by assessing relevant physical traits and symptoms. They are weighed based on their diagnostic importance and scored as such. A weighted sum of the responses is computed to generate a score for each disease, providing a quantitative estimate of the likelihood of infection. To improve accuracy, this domain knowledge algorithm's score is combined with a deep learning model's output, each contributing 50% to the final diagnosis. This hybrid approach integrates expert knowledge and AI, improving reliability in detecting skin diseases in dogs.

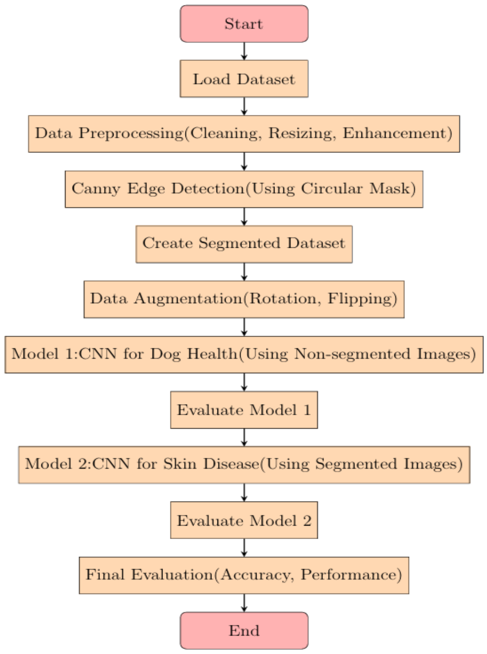

Fig. 2. Model Architecture

The weighting of the questions in the algorithm was created from consultation with veterinary experts and online resources, prioritizing their importance in disease identification. Questions with direct impact on the diagnosis were weighted 0.5, and those with intermediate impact were weighted 0.2. Other questions were weighted 0.03. Users were given three response alternatives: “Severe”, “Moderate”, and “None” which corresponded to scores of 1, 0.5, and 0, respectively.

Some of the questions and respective weights used in the survey are as follows:

i) Does your dog experience extreme itchiness, especially around the ears, chest, belly, or hind legs?

Ringworm: Itching is common but tends to be milder.

Mange: Intense itching and scratching are much more severe.

Weight for Ringworm: 0.03

Weight for Mange: 0.5

ii) Are there any lesions that resemble a red ring in general?
Ringworm: Ring-shaped lesions with clear edges and a lighter center.
Mange: Lesions are less defined, and there may be no circular pattern or clear borders.
Weight for Ringworm: 0.5
Weight for Mange: 0.03
iii) Does the affected region seem to be smelling musty or odd to you?
Ringworm: Often odorless.
Mange: The skin may become foul-smelling in some cases.
Weight for Ringworm: 0.03
Weight for Mange: 0.2

The participants' responses are multiplied with the assigned weights for each of the questions from the provided algorithm and a projected score is obtained for each disease. The results of these calculations are added to produce an expected score for each disease. The condition with the highest score value will be the final diagnosis. This approach allows us to quantify the odds of each disease, given the physical traits of the dog in question.

IV. Results and Discussion

The results of the Canine Dermal Analyser project demonstrate the effectiveness of the proposed methodology in accurately detecting skin diseases in dogs, specifically focusing on mange and ringworm. The training process involved a comprehensive dataset of images, which were meticulously preprocessed to enhance their quality and ensure that the CNN model could learn effectively from the data.

The training accuracy of the CNN model showed a steady improvement throughout the epochs, surpassing 98% by the 20th epoch and nearing 100% towards the end of the training process. This increase in accuracy shows that the model has properly learned the distinguishing features of the lesion data which were segmented, helping it to accurately differentiate between the two targeted skin diseases. Fig. 3 shows the accuracy of the training in the epochs for the classification model.

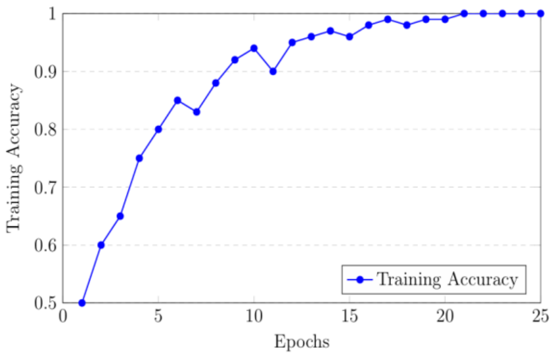

Fig. 3. Training Accuracy Over Epochs for Classification Model

In addition to training accuracy, the validation loss was closely monitored. Initially, the training loss started at a higher value but decreased rapidly, indicating effective learning. Both training and validation losses stabilized close to zero, suggesting that the model was well-fitted and exhibited minimal overfitting. This stability in loss values is crucial as it reflects the model's ability to generalize well to unseen data. Fig. 4 shows the training and validation loss over epochs for the classification model.

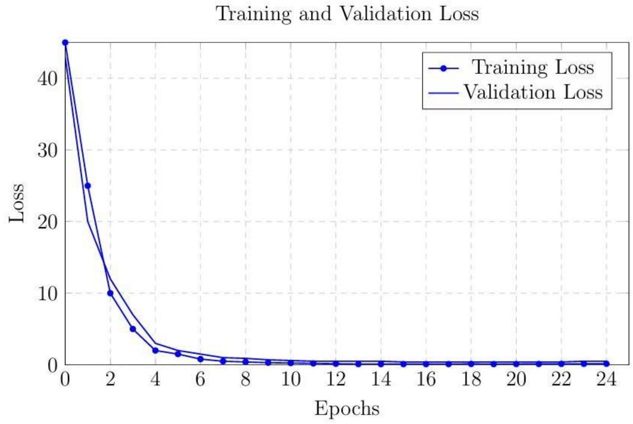

Fig. 4. Training and Validation Loss Over Epochs for Classification Model

Furthermore, a binary classification model was developed to detect whether a dog is diseased or not. This model quickly achieved high accuracy, reaching over 90% within the first few epochs and nearing 100% as training progressed. The consistent performance at near-perfect accuracy in later epochs indicates that the model effectively learned and fitted the training data, suggesting strong classification capability for the task. Fig. 5 shows the training accuracy over epochs for the binary classification model.

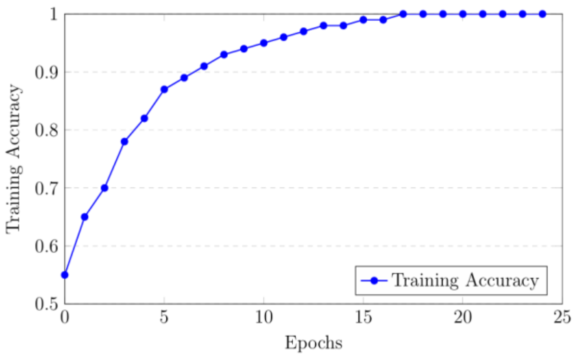

Fig. 5. Training Accuracy Over Epochs for Binary Classification Model

The training and validation loss for the binary classification model also demonstrated a rapid decrease within the initial epochs, indicating effective learning. After approximately ten epochs, both the training and validation losses stabilized close to zero, suggesting that the model achieved a high level of accuracy and generalization. Fig. 6 shows the training and validation loss over epochs for the skin disease detection model. The outputs of both models were evaluated to assess their performance in classifying the images accurately. The results indicate that the integration of the CNN model with the weighted scoring algorithm based on the questionnaire survey significantly enhances the diagnostic capabilities of the system. The combination of visual analysis and user-reported symptoms provides a comprehensive approach to diagnosing canine skin diseases.

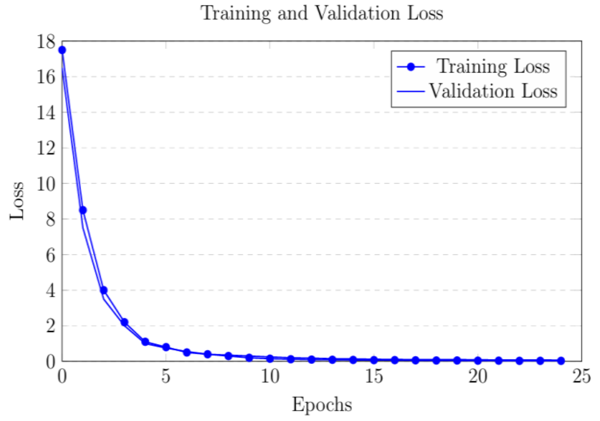

Fig. 6. Training and Validation Loss Over Epochs for Skin Disease Detection Model

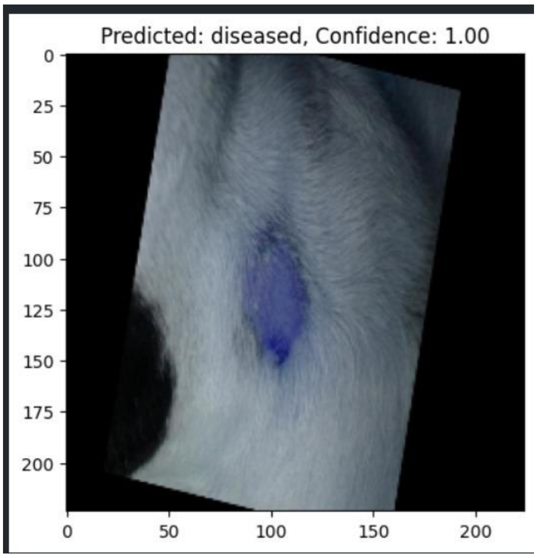

Fig. 7. Output of Binary Classification of Diseased or Not Model

Fig. 7 shows the output of binary classification of diseased or not model. Fig. 8 shows the output of binary classification of segmented skin lesion model.For disease identification using the weighted scoring Algorithm, considering the lesion in Fig. 7. The weighted scoring algorithm was employed to determine the most probable skin disease by analyzing responses to specific questions. The responses were selected based on characteristic symptoms. For itchiness, the response "Moderate" resulted in a Ringworm score of 0.015 and a Mange score of 0.25. The presence of circular or ring-like hair loss was rated as "Severe", contributing 0.5 to Ringworm and 0.03 to Mange. Thick yellow crusts or oily skin, marked as "Moderate", contributed 0.015 to Ringworm and 0.25 to Mange. Brittle claws or coat changes, rated "Severe", added 0.5 to Ringworm and 0.03 to Mange. A musty or strange odor, rated "None", resulted in 0.0 for both diseases. Red ring-like lesions, answered as "Severe", contributed 0.5 to Ringworm and 0.03 to Mange. The final weighted scores were 1.53 for Ringworm and 0.59

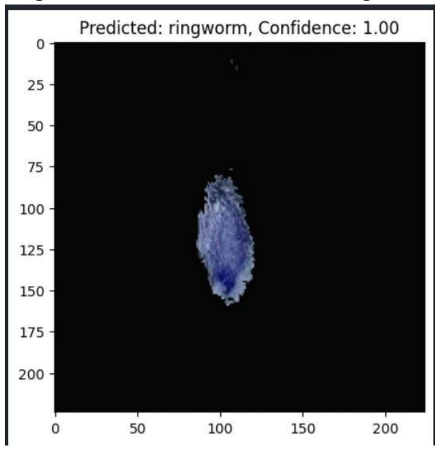

Fig. 8. Output of Binary Classification of Segmented Skin Lesion Model

for Mange as shown in Fig. 9, indicating that Ringworm is the most probable diagnosis. The responses was designed to emphasize Ringworm's defining traits, including ring-shaped hair loss, brittle claws, and distinct red-ring lesions, ensuring an accurate classification.

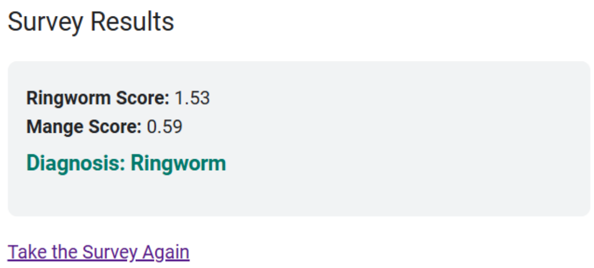

Fig. 9. Output of Weighted Scoring Algorithm based Survey

In conclusion the integration of the CNN model with the weighted scoring algorithm significantly enhances the validation process for lesion detection and disease classification. The deep learning model, trained on a high-quality dataset, achieved over 98% accuracy within 20 epochs, demonstrating its ability to accurately differentiate skin diseases. Additionally, the weighted scoring algorithm refines predictions by incorporating symptom-based evaluations. This hybrid approach improves diagnostic precision, ensuring a comprehensive and reliable system for canine skin disease detection.

V. CONCLUSION

The success of our project has shown the reliability of convolutional neural networks (CNNs), showing that they are capable of accurate detection of skin diseases such as mange and ringworm in dogs. By integrating deep learning and domain knowledge-based weighted scoring for supervised machine algorithm, we proposed an intelligent diagnosis system that improves veterinary medicine. The mobile-friendly nature of the system makes it accessible to veterinarians as well as pet owners and allows early detection and timely treatment.

Future developments will involve improvements of the model's accuracy by training it along with the introduction of more varieties of skin diseases. In addition, a chat bot for severity assessment and a web user interface will be able to serve users in real time. The deployment of the flask model will allow for easy scalability and communication of the result. Our project is thus a major step toward enhancing pet healthcare through a synergistic integration of deep learning, domain knowledge, and interactive applications through AIdriven diagnostics.

REFERENCES

[1] S. Hwang, H. K. Shin, J. M. Park, B. Kwon, and M.-G. Kang, "Classification of dog skin diseases using deep learning with images captured from multispectral imaging device," Molecular & Cellular Toxicology, vol. 18, no. 3, pp. 299–309, 2022.

[2] N. Thoutam, I. Mandloi, A. Kumari, S. Sonule, and V. Torawane, "Detection and Classification of Dog Skin Disease Using Deep Learning", Sandip Institute of Technology and Research Center, Nashik, India, 2023.

[3] N. Kudahetty, R. De Silva, T. Piyadasa, "An Intelligent Approach to Identify Household Canine Dermatology", International Research Conference of Sri Lanka Technology Campus, Colombo, 2023.

[4] R. M. M. Mellores, J. C. D. Salvoza, S. O. Flores, J. C. T. Arroyo, and A. J. P. Delima, "Android-based Application Utilizing Image Processing with Artificial Neural Network for Detecting Ringworm and Yeast Infections for Dogs Using Neuroph Framework", College of Computing Education, University of Mindanao, College of Engineering, Technology and Management, Cebu Technological University-Barili Campus, vol. 9, no. 3, 2020.

[5] R. Rathnayaka, K. Anuththara, R. Wickramasinghe, P. Gimhana, L. Weerasinghe, and G. Wimalaratne, "Intelligent system for skin disease detection of dogs with ontology based clinical information extraction," IEEE 13th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), pp. 0059–0066, IEEE, 2022.

[6] R. Sonia, J. Joseph, D. Kalaiyarasi, N. Kalyani, A. S. A. L. G. Gupta,
G. Ramkumar, H. S. Almoallim, S. A. Alharbi, and S. S. Raghavan, "Segmenting and classifying skin lesions using a fruit fly optimization algorithm with a machine learning framework", Automatika, vol. 65, no. 1, pp. 217-231, 2023.

[7] A. Kolli, Q. Wei, and S. A. Ramsey, "Predicting time-to-healing from a digital wound image: A hybrid neural network and decision tree approach improves performance," Computation, vol. 12, no. 3, p. 42, 2024.

[8] O. Jaiyeoba, E. Ogbuji, O. T. Yomi, and F. Oladipo, "Development of a Model to Classify Skin Diseases Using Stacking Ensemble Machine Learning Techniques", Journal of Computing Theories and Applications, vol. 2, no. 1, pp. 22–38, 2024.

[9] A. Smith, P. W. Carroll, S. Aravamuthan, E. Walleser, H. Lin, K. Anklam, D. Dopfer, and N. Apostolopoulos, "Computer Vision Model¨ for the Detection of Canine Pododermatitis and Neoplasia of the Paw", Veterinary Dermatology, vol. 35, no. 2, pp. 138–147, 2024.

[10] E. H. I. Eliwa, A. M. E. Koshiry, T. A. El-Hafeez, and H. M. Farghaly, "Utilizing Convolutional Neural Networks to Classify Monkeypox Skin Lesions", Scientific reports, vol. 13, no. 1, p. 14495, 2023.

[11] R. Mittal, F. Jeribi, R. J. Martin, V. Malik, S. J. Menachery, and J. Singh, "DermCDSM: Clinical Decision Support Model for Dermatosis Using Systematic Approaches of Machine Learning and Deep Learning", IEEE Transactions on Biomedical Engineering, 2024.

[12] F. Bagheri, M. J. Tarokh, and M. Ziaratban, "Skin Lesion Segmentation Based on Mask RCNN, Multi Atrous Full-CNN, and a Geodesic Method", International Journal of Imaging Systems and Technology, vol. 31, no. 3, pp. 1609–1624, 2021.

[13] D. K. Nguyen, T. -T. Tran, C. P. Nguyen and V. -T. Pham, "Skin lesion Segmentation based on Integrating EfficientNet and Residual block into
U-Net Neural Network," 2020 5th International Conference on Green Technology and Sustainable Development (GTSD), Ho Chi Minh City, Vietnam, 2020, pp. 366-371.

[14] E. Girma, "Identify Animal Lumpy Skin Disease Using Image Processing and Machine Learning", PhD diss., St. Mary's University, Addis Ababa, Ethiopia, 2021.

[15] Y. Saroja, V. S. Varshitha, S. P. C. Rao, V. N. S. Likith, and G. S. N. Murthy, "The Pet Breed Detection and Skin Disease Detection Using Image Processing," International Journal of Research Publication and Reviews, Vol 5, no 5, pp. 1774-1783, 2024.