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A Review of Machine Learning Approaches for Canine Skin Disease Detection Using Image Processing Techniques

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***Abstract*—This literature review explores recent advancements in machine learning and image processing techniques for the detection of canine skin diseases. Sixteen studies were analyzed, focusing on different methodologies such as convolutional neural networks (CNNs), support vector machines (SVMs), and deep learning frameworks. The review highlights the applications, advantages, and limitations of these approaches in terms of accuracy, efficiency, and applicability. This work aims to provide insights into the current state of research and identify potential areas for future exploration.**

***Index Terms*—Canine skin disease detection, image processing, artificial neural networks, machine learning, deep learning, CNN, SVM.**

I. Introduction

The detection and classification of skin diseases in dogs have seen significant improvements with the advent of machine learning and image processing technologies. Traditional diagnostic methods rely heavily on veterinary expertise, which may not always be accessible. To address these challenges, various studies have explored the use of machine learning algorithms, particularly convolutional neural networks (CNNs), artificial neural networks (ANNs), and support vector machines (SVMs), to automate the diagnosis of skin conditions such as ringworm, yeast infections, and other dermatological ailments.

II. Machine Learning Techniques for Skin Disease Detection

A. Artificial Neural Networks (ANNs)

The use of Artificial Neural Networks (ANNs) has been pivotal in building machine learning models to classify skin diseases in dogs. Mellores et al. [1] developed an Android-based application using the Neuroph framework to detect and classify localized skin diseases such as ringworm and yeast Zinfections. This application employed an ANN to process captured images of affected skin lesions, utilizing OpenCV for image preprocessing and feature extraction. The ANN was trained with 200 images of each disease, and the system demonstrated high accuracy, achieving 97-98% prediction rates for correctly classifying skin infections. The study highlights the feasibility of using mobile devices for at-home diagnostics, leveraging image processing techniques to assist dog owners in early detection and care.

By implementing OpenCV's image stitching and segmentation tools, the application successfully analyzed captured images, allowing it to provide a detailed diagnosis and recommended treatments. The success of this model in a mobile environment underscores the potential for further development in portable veterinary diagnostic systems [1].

B. Convolutional Neural Networks (CNNs)

Several studies have applied convolutional neural networks (CNNs) to detect various skin conditions in dogs. Thoutam et al. [10] used transfer learning with pre-trained models (MobileNetV2 and InceptionV3) to classify dog skin diseases, achieving validation accuracies of 94% and 98%, respectively. Similarly, Girma et al. [5] employed CNNs for deep feature extraction and used an SVM for classification, attaining an accuracy rate of 95.7%. The study utilized CNN's architecture to learn distinguishing features of disease from images, with several convolutional layers that reduce the spatial dimensions of the image while retaining the most significant features for classification.

C. YOLOv8 Architecture

The YOLOv8 architecture, as detailed in the document, is a state-of-the-art object detection model from the You Only

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Look Once (YOLO) series. It is highly efficient for real-time object detection tasks. The architecture comprises three main components:

Backbone: The backbone utilizes a custom CSPDarknet53 convolutional neural network (CNN) for feature extraction from input images. The cross-stage partial (CSP) connections enhance the flow of information between layers, which improves accuracy.

Neck: The neck is responsible for merging feature maps at different stages, combining high-level semantic features with low-level spatial details. YOLOv8 introduces the C2f module instead of the traditional Feature Pyramid Network (FPN), which is particularly effective for detecting small objects.

Head: sThe head performs predictions by outputting bounding boxes, objectness scores, and class probabilities. The combination of these elements generates the final detection results.

In the context of pet breed detection and skin disease diagnosis, YOLOv8 excels due to its real-time detection capabilities. The model has been integrated with image processing techniques and CNNs to provide accurate and timely identification of breeds and skin conditions. The efficiency of YOLOv8 makes it a valuable tool in veterinary medicine, offering a fast and accurate method for detecting pet breeds and diagnosing skin diseases [2].

D. Disease Severity Detection

The severity level detection of skin diseases in dogs is a process that utilizes image processing techniques to classify the extent of the condition into predefined levels such as none, moderate, and severe. This is achieved through a series of steps that include image acquisition, preprocessing (filtering, rotation, segmentation), feature extraction (focusing on redness, dandruff, and hair loss), and classification. The classification is typically done using machine learning models, such as Convolutional Neural Networks (CNNs), which are trained to recognize patterns in the extracted features that correspond to different severity levels.

The training process involves feeding the model with annotated images, allowing it to learn the visual characteristics associated with each severity level. Once trained, the model can then be applied to new images to predict the severity level of the skin disease. This automated approach aims to assist veterinarians and pet owners in making informed decisions about the treatment and management of skin conditions in dogs [9].

E. Ontology-based Information Extraction from Data Resources of Skin Diseases

An ontology-based information extraction system has been developed to aid in skin disease detection in dogs by structuring and extracting clinical data. This system leverages a domain-specific ontology to provide comprehensive and consistent information on skin disorders. The ontology uses disjoint classes and existential restrictions to maintain logical consistency and is validated using Prote´ge´ 5.5 and the HermiT reasoner.

The ontology follows a top-down approach and uses multiple inheritance to enhance knowledge representation. Implemented in OWL2, it is integrated into a mobile application that includes an AI chatbot with sentiment analysis capabilities. The app provides users with quick and accurate responses to inquiries about diagnosis techniques, symptoms, infections, causes, affected areas, treatments, and prevention methods for dog skin diseases. This approach ensures that the system delivers relevant and structured information to dog owners, helping them manage their pets' skin conditions more effectively [9].

F. Hybrid and Ensemble Learning Approaches

Kolli et al. [6] utilized a hybrid model combining deep neural networks SegNet, U-Net with decision tree regression to predict wound healing time from images. It uses CNN-based image segmentation and tissue classification to enhance prediction accuracy. Hwang et al. [11] combined multiple CNN architectures, including InceptionNet, ResNet, and DenseNet, for classifying skin diseases from multispectral images. The study found that using consensus models built from the best-performing individual models enhanced the overall accuracy and robustness. Eliwa et al. [15] optimized CNN hyperparameters using the Grey Wolf Optimizer (GWO), resulting in improved classification performance of monkeypox skin lesions, which could be adapted to canine skin disease detection.

G. Hyperparameter Optimization

In the realm of machine learning, selecting the optimal hyperparameters is crucial for the performance of a model. Hyperparameters are the parameters set before the learning process begins, and their values can significantly influence the behavior and accuracy of the learning algorithm. The process of finding the best set of hyperparameters is known as hyperparameter optimization or hyperparameter tuning. Research by Sonia et al. [3]discusses the use of the Fruit Fly Optimization Algorithm (FOA) to optimize the hyperparameters of a Support Vector Machine (SVM) model for the classification of skin lesions. The study introduces an integrative approach that leverages the Fruit Fly Optimization Algorithm to optimize the Support Vector Machine hyperparameters, specifically the penalty ratio and the width of the kernel function.

As depicted in Figure 1, the Fruit Fly Optimization Algorithm consistently improves the model's performance across iterations, surpassing other algorithms like the Moth Flame Optimization Algorithm (MFO), Bat Algorithm (BA), Flower Pollination Algorithm (FPA), and Particle Swarm Optimization (PSO) in terms of the F1 score. The steady increase observed in each iteration demonstrates the efficiency of the Fruit Fly Optimization Algorithm in hyperparameter optimization, particularly when compared to alternatives such as the Moth Flame Optimization Algorithm, which shows slower growth, or the Bat Algorithm, which plateaus early. The superior performance of the Fruit Fly Optimization Algorithm is evident

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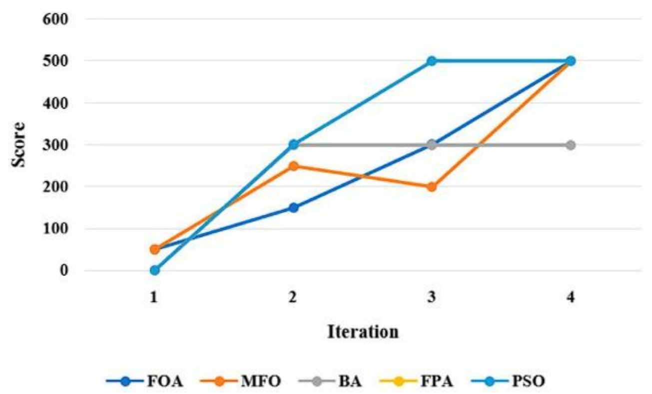

Fig. 1. FOA convergence curve [3].

as it achieves the highest score in the final iteration, making it a promising choice for this optimization task.

Grey Wolf Optimization (GWO) mimics the hunting strategy and social hierarchy of grey wolves to solve optimization problems. The wolves are categorized as alpha (α), beta (β), delta (δ), and omega (ω), where α, β, and δ guide the pack toward the optimal solution (prey). The positions of all wolves (solutions) are updated based on the best positions of α, β, and δ wolves.

The process continues until a stopping criterion is met, and the best solution is the one closest to the prey, effectively solving the optimization problem. [15]. It searches for the optimal set of hyperparameters by mimicking the hunting behavior of wolves. GWO adjusts these hyperparameters iteratively, balancing exploration and exploitation, to maximize the model's accuracy and minimize errors efficiently.

III. Image Processing Techniques for Feature Extraction and Classification

A. Image Preprocessing and Enhancement

Several studies emphasized the importance of preprocessing techniques for improving model accuracy. Techniques such as noise removal, image resizing, and normalization were used to prepare datasets for analysis. Nguyen et al. [8] integrated EfficientNet and ResNet components into a U-Net neural network, enhancing the segmentation performance of skin lesions by balancing the network's feature extraction and localization capabilities. EfficientNet improves feature extraction by scaling the network's depth, width, and resolution, while ResNet blocks mitigate overfitting and vanishing gradient issues during upsampling. This hybrid approach ensures efficient feature extraction and precise localization, leading to better segmentation performance, particularly for skin lesions.

IV. Segmentation Techniques

Segmentation of skin lesions is crucial in distinguishing affected regions from the surrounding healthy tissue, which forms the basis for accurate feature extraction and classification in machine learning frameworks. Among the various segmentation methods, the use of a circular kernel in morphological operations has been identified as highly effective due to the prevalence of circular or oval shapes in many skin lesions.

The circular kernel is applied in a morphological closure procedure to improve segmentation accuracy by aligning the identified regions closely with the actual boundaries of the lesions. This kernel is chosen because it matches the typical shape of skin lesions, enabling effective isolation of the lesion areas from the background. The morphological closure operation consists of dilation followed by erosion using the circular kernel:

$$S_{closed} = (S \oplus K) \ominus K \tag{1}$$

where S is the segmented image, K is the circular kernel, $\oplus$ denotes the dilation operation, and $\ominus$ denotes the erosion operation. The use of the circular kernel ensures that the boundaries of the identified lesion regions align closely with their actual shapes, enhancing segmentation accuracy.

Fig. 2. Preprocessing step for image enhancement [1].

Segmentation is a crucial step in image analysis where the goal is to isolate and separate the object of interest (in this case, the skin lesion) from the rest of the image. This process involves assigning a label to every pixel in the image to distinguish between different objects or regions. Mellores et al. [1] used segmentation techniques in their Android-based application to focus on the skin lesion and prepare the image for further analysis. The figure in the study (Figure 2) illustrates how segmentation is applied, showing how the lesion is separated from surrounding skin for accurate diagnosis.

Similarly, the preprocessing step shown in Figure 1 demonstrates the initial step of filtering and enhancing the captured image before segmentation. Preprocessing includes noise removal and Gaussian operations to smoothen the image, removing irrelevant elements such as hairs and dirt to improve the quality of analysis.

Bagheri et al. [7] developed a robust skin lesion segmentation method using Mask R-CNN for initial detection, followed by a multi-atrous full CNN (MAFCNN) to refine the segmentation. To further enhance boundary accuracy, they applied a geodesic segmentation method, which focuses on fine-tuning lesion edges. Key challenges such as lesion variability in shape, size, and noise (e.g., hair, ruler marks) were discussed, offering insights into how such techniques could be adapted for identifying and classifying skin diseases in dogs.

Furthermore, circular kernel operations, such as those presented by Nguyen et al. [8], have been shown to enhance

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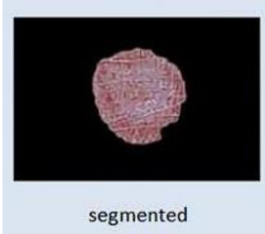

Fig. 3. Segmentation process in the Android-based application for detecting dog skin diseases [1].

segmentation accuracy, particularly in medical image analysis. The circular kernel isolates lesion boundaries more precisely, improving the overall accuracy of the classification.

V. Challenges and Future Directions

A. Challenges

Despite the advancements, several challenges remain. The reliance on high-quality images and the complexity of deep learning models often require significant computational resources, which may limit their deployment on mobile or edge devices. Moreover, the potential for overfitting due to small datasets, as highlighted by multiple studies, indicates a need for larger and more diverse data collections.

B. Future Research Opportunities

Future research could focus on developing lightweight models optimized for deployment on mobile devices, such as the Tiny YOLOv4 used by Smith et al. [13]. Additionally, integrating real-time data collection and cloud-based processing could enhance the usability of these applications in veterinary practice. Further exploration of hybrid models and ensemble learning techniques may also improve the robustness and accuracy of detection systems.

VI. Conclusion

The reviewed studies demonstrate significant progress in applying machine learning techniques for canine skin disease detection using image processing. While current models show high accuracy, especially in controlled environments, future research should address challenges related to data quality, model complexity, and computational requirements. There is potential for improving diagnostic tools, making them more accessible and efficient for real-world veterinary applications.

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