JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

CANAI: AI-ASSISTED CANINE DISEASE RECOGNITION SYSTEM

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Abstract: The identification and diagnosis of diseases in dogs have historically depended on the skills of veterinarians, frequently involving labor-intensive manual methods. This study presents an AI-driven system designed for the automatic identification of canine illnesses through deep learning approaches, particularly utilizing Convolutional Neural Networks (CNNs). The system analyzes images of dogs to diagnose various diseases, trained on a comprehensive dataset of labeled canine images. The study addresses challenges such as image quality variability, the need for high-quality annotated datasets, and model optimization for mobile and real-time deployment. This system investigates the integration of IoT tools to improve monitoring and diagnostic processes in veterinary care. The findings highlight how AI can enhance disease identification by enabling faster and more accurate diagnostics in canine health management.

Keyword- **Artificial Intelligence, Canine Disease Recognition, Convolutional Neural Networks, Veterinary Diagnostics, Image Classification.**

I. INTRODUCTION

Ensuring the health of dogs is fundamental to the well-being of companion and service animals worldwide, however, diagnosing diseases often depends on traditional veterinary knowledge, which can be labor-intensive, costly, and susceptible to human mistakes. The early identification of diseases is crucial for successful treatment and enhancing recovery opportunities, but standard diagnostic approaches—based on clinical symptoms or lab assessments—face restrictions related to availability, expense, and the necessity for prompt action. Furthermore, the rising incidence of zoonotic illnesses and intricate health issues complicates the accuracy of realtime diagnosis. To tackle these challenges, AI-based solutions for disease identification in dogs, especially through image analysis and machine learning, have emerged as a hopeful alternative.

Canine diseases, which can be triggered by pathogens like bacteria, viruses, fungi, and parasites, often manifest as skin lesions, coughing, vomiting, and lethargy, which are visually detectable. However, early-stage symptoms are sometimes subtle and not easily recognized by owners or general veterinarians, making diagnosis difficult. Traditional methods of diagnosis may also be slow, with delays in identifying the exact cause of illness. Alternatively, machine learning (ML) and deep learning (DL) techniques- especially Convolutional Neural Networks (CNNs)- offer a promising solution by facilitating rapid and accurate disease detection using visual data from dog images.

By training CNN architectures trained on large datasets of dog images, AI systems can automatically detect and classify diseases based on visual symptoms. These systems are capable of identifying diseases such as parvovirus, mange, rabies, or tick-borne diseases, that can be challenging for non-specialists to identify accurately. The models are designed to process high-resolution dog images, offering diagnostic precision that often surpasses human performance. This method not only improves diagnostic speed and accuracy but also delivers prompt suggestions for veterinary intervention, helping to minimize the reliance on expensive laboratory procedures and avoid unnecessary treatments.

The system is built to integrate seamlessly with mobile applications or smart devices, allowing pet owners and veterinarians to quickly capture and upload images for diagnosis. Once an image is uploaded, the AI model processes it to detect potential diseases, providing immediate feedback with a suggested diagnosis. This technique brings multiple benefits, such as quicker diagnostic results, minimized chances of human error, and improved access to veterinary services- particularly valuable in remote or under-resourced areas.

In summary, AI-based disease recognition systems for canines represent a transformative advancement in veterinary care, offering improved diagnostic accuracy, speed, and cost-efficiency. By leveraging deep learning and advanced image analysis, these systems have the potential to significantly enhance early disease detection, leading to better health outcomes for dogs and improving the overall efficiency of veterinary services.

II. LITERATURE REVIEW

The use of artificial intelligence (AI) in veterinary care has created new possibilities for non-invasive, efficient, and automated disease diagnosis in animals, especially in canines. Recent studies highlight the increasing reliance on deep learning (DL) techniques, particularly convolutional neural networks (CNNs), for analyzing image-based data to detect abnormalities in pets. de Oliveira et al. (2023) present a comprehensive review of AI applications across various veterinary imaging modalities—such as radiographs, ultrasounds, and MRIs—illustrating how these technologies enhance diagnostic precision and reduce dependence on human interpretation. Their study emphasized that AI can be instrumental in early disease detection and can assist veterinarians by flagging abnormalities that may not be easily visible in standard diagnostics. While the potential of these systems is vast, the authors also noted the importance of ethical AI deployment, stressing transparency in algorithmic decision-making and the need for human oversight.

Further extending this application, Yoon et al. (2022) explored CNN-based models specifically trained to interpret canine thoracic radiographs. Their research revealed that deep learning models not only demonstrated high accuracy in detecting pulmonary and cardiac abnormalities but also surpassed traditional machine learning models in sensitivity and precision. These results solidify CNNs as the preferred architecture for veterinary diagnostic imaging. Another critical work by Hwang et al. (2022) involved the use of multispectral imaging data combined with CNNs to classify canine skin diseases. By incorporating data from non-visible light spectra, this method improved image contrast, enabling more effective detection of skin lesions compared to standard RGB imaging. This highlights the potential of multimodal image inputs in advancing veterinary diagnostics.

The overarching theme across literature is that deep learning models outperform traditional ML methods—such as support vector machines (SVM) and decision trees— primarily because of their capability to autonomously extract significant features from raw image data. For instance, Johnson et al. (2022) conducted a comprehensive review of various studies and underscored the importance of large, annotated datasets and model interpretability, noting that deep learning models tend to generalize better and offer more robust diagnostic accuracy than models dependent on hand-crafted features. In contrast, Smith et al. (2024) cautioned against uncritical adoption of AI in clinical settings, pointing out issues like bias from unbalanced datasets, lack of veterinary-specific image repositories, and challenges in interpreting CNN decision boundaries—especially in life-critical diagnoses.

Beyond diagnostics, researchers have also started to explore the practical implementation of AI systems in real-time scenarios. For example, integrating AI-powered diagnostic systems with mobile applications or embedded devices in veterinary clinics or animal shelters could allow for rapid triaging and early disease detection. Studies suggest that such systems could enhance animal welfare and ease the workload of veterinary professionals. However, studies stress the importance of training models on diverse datasets that include breed variations, environmental conditions, and disease stages to ensure high generalization capability. Moreover, the successful deployment of these tools in the field also demands user-friendly interfaces and scalable infrastructure.

In conclusion, the reviewed literature consistently supports deep learning—particularly CNNs—as the core AI method for imagebased diagnosis of canine diseases. While multispectral imaging and hybrid models (like ensemble learning or attention mechanisms) are being actively explored, the current state-of-the-art leans heavily on robust CNN architectures trained on large, well-labeled datasets. The collective findings of these studies highlight not only the transformative potential of AI in veterinary care but also the importance of interdisciplinary collaboration, transparent validation, and ethical deployment of AI to enable its practical use.

Key Findings and Trends

- ✓ Deep Learning Superiority: CNNs excel in accuracy and feature extraction.
- ✓ Traditional ML Value: ML remains useful for smaller datasets and limited resources.
- ✓ Dataset Dependency
- ✓ Deployment Challenges: Image variability (lighting, noise) impacts accuracy.
- ✓ Need for Lightweight Models: Mobile and real-time performance optimization required.
- ✓ IoT Integration: Enhances real-time monitoring and care.
- ✓ Hybrid Approaches: Combining traditional techniques with AI improves robustness.
- ✓ Evaluation Metrics: Standardized benchmarks needed for comparison.
- ✓ Ethical Considerations: Ensuring transparency and trust in AI decision-making.

III. METHODOLOGY

The development of the AI-based canine disease recognition system followed a systematic pipeline involving collecting data, preparing it, training the model, evaluating its performance and planned deployment. The system aims to accurately identify four specific canine skin conditions—fungal infections, dermatitis, hypersensitivity, and ringworm—by analyzing images of affected dogs using deep learning.

To ensure the creation of a reliable and diverse dataset, images of dogs were sourced from various platforms. These included open access veterinary dermatology image repositories, academic datasets, and curated samples obtained through collaboration with veterinary professionals. Additionally, publicly available images from trusted platforms were vetted manually to ensure medical accuracy and clarity of symptoms. The diseases were chosen based on prevalence and visual detectability through skin features. Each image was categorized into one of five classes: fungal infection, dermatitis, hypersensitivity, ringworm, and healthy. The "healthy" class was crucial not only to act as a baseline for model comparison but also to help the system avoid false positives. This category was essential for training the model to distinguish between normal and diseased skin based on texture, pattern, and coloration differences. To enhance the clarity of the classification approach, sample images will be presented in the methodology section. These include side-by-side comparisons of diseased and healthy canine images. For example, an image showing fungal infection symptoms (such as circular hairless patches and scaling) will be displayed adjacent to an image of healthy fur in the same region. These visuals highlight the subtle differences that the model is trained to recognize and help readers understand the basis of class separability.

Healthy

Fungal Infection

Healthy

Dematitis

Healthy

Hypersensitivity

Healthy

Ringworm

All collected images were resized to 224×224 pixels to align with the input requirements of deep convolutional neural networks such as ResNet and MobileNet. Pixel normalization was performed, scaling values between 0 and 1 to ensure faster convergence during training. A robust augmentation strategy was employed to simulate real-world variability—this included rotation, horizontal flipping, random zoom, brightness adjustments, and minor blurring. These augmentations improve generalization by making the model resilient to different poses, lighting conditions, and backgrounds commonly encountered in real-life pet photos. Additionally, noise reduction methods like Gaussian blur and median filters were selectively used to minimize visual artifacts that could negatively impact learning performance. All class labels were encoded using one-hot encoding to support multi-class classification tasks.

For the model backbone, ResNet-50 was chosen due to its high accuracy and its residual connection architecture, which allows deeper networks to be trained effectively without vanishing gradient problems. This helps in preventing vanishing gradients and allows the model to retain performance even with deeper layers. MobileNet is also being considered as an alternative lightweight model for mobile deployment. The training was conducted using categorical cross-entropy loss, optimized via the Adam optimizer. Learning rate decay and early stopping strategies were implemented to improve convergence and prevent overfitting. The dataset was partitioned into training (70%), validation (15%), and test (15%) sets using stratified sampling to preserve class distribution across all subsets.

The effectiveness of the model was assessed using evaluation metrics like accuracy, precision, recall, F1-score, and the confusion matrix. Special emphasis was placed on precision and recall for disease detection, as reducing false negatives—cases where the model fails to identify an existing condition—is especially crucial in ensuring timely and reliable diagnosis. The final model was exported in a format suitable for web-based deployment. For deployment, the trained model will be integrated into a web interface where users (such as pet owners or veterinarians) can upload dog images and receive classification results. The interface will display a visual overlay indicating the predicted class, along with confidence levels and the option to view healthy reference images for comparison. This makes the system more interpretable and trustworthy for end-users.

If the dataset is expanded in the future, whether by including additional diseases, age-specific variations, or breeds, the methodology will be adapted accordingly. This may involve re-training the model, updating label encoding, retraining augmentation strategies, or selecting a more suitable architecture. These changes will be explicitly documented to ensure consistency and reproducibility of results.

IV. EXPECTED OUTPUT

Building on the described methodology and insights gathered from previous research, the AI-driven canine skin disease detection system is expected to yield promising outcomes. Leveraging the ResNet-50 model, the system aims to deliver high classification accuracy—potentially exceeding 90%— in identifying and differentiating between four major skin disorders: fungal infections, dermatitis, hypersensitivity, and ringworm, along with distinguishing them from healthy skin conditions. This performance is anticipated to hold even when dealing with real-world images sourced from diverse environments and captured under varying lighting conditions. The model's strong generalization ability is supported by extensive use of data augmentation and noise reduction techniques applied during preprocessing.

Secondly, the system is developed to offer quick and dependable diagnostic assistance for both pet owners and veterinary practitioners. Once available as a mobile or web-based application, users will have the ability to upload images of their dog's skin and receive prompt analysis that includes the predicted condition, a confidence percentage, and visual indicators like comparison images showing healthy skin. This feature is intended to facilitate early recognition of skin conditions and promote timely veterinary care, especially in regions with limited access to professional services. Moreover, the inclusion of both healthy and diseased categories ensures a well-rounded diagnostic process that reduces the chances of false positives and avoids unnecessary treatments. A user-friendly interface enhances the experience by offering clearly marked results and optional educational content, helping users better understand and monitor their pet's skin health.

In addition, the system is built with adaptability and scalability in mind. As new images and conditions are introduced, the framework allows for straightforward retraining and expansion without needing major changes. This future-proofs the system and broadens its capacity to handle more canine health issues over time. Since the model is optimized for lightweight and fast performance, it can also be deployed on resource-constrained hardware like smartphones or Raspberry Pi devices, allowing for offline use in rural or low-connectivity areas. Ultimately, this project provides a solid starting point for bringing artificial intelligence into veterinary diagnostics. By integrating deep learning with accessible digital tools, it opens the door to a more advanced and intelligent approach to pet healthcare in both homes and clinical settings.

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