Multi-Species Skin Disease Detection and Treatment Advisor Using Transfer Learning

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ABSTRACT: Animal skin diseases are a prevalent issue affecting domestic and farm animals, leading to health deterioration and economic losses if left undiagnosed or untreated. This project proposes a Flask-based web application for real-time and offline detection of skin diseases in animals, specifically targeting dogs, cats, and cattle. The system allows users to either upload an existing image or capture a live image of the affected animal skin. After selecting the animal type, a corresponding pre-trained deep learning model using transfer learning is activated for inference. The models are fine-tuned for high-accuracy classification of common skin conditions in the respective species.

Upon detecting a skin disease, the application automatically displays the name of the disease along with a recommended remedy based on veterinary guidelines and curated datasets. The system is designed to be user-friendly, accessible to both veterinarians and animal owners, and functional on low-resource devices. By integrating computer vision with AI-driven diagnosis and remedy mapping, the system aims to enhance early detection, support animal welfare, and minimize dependency on manual examination. Future improvements include expanding species support and enabling multilingual remedy support.

KEYWORDS: Animal Skin Disease, Deep Learning, Flask Application, Image Classification, Transfer Learning, Veterinary Remedies, Real-Time Detection.

1. INTRODUCTION: Livestock and companion animals such as cattle, dogs, camels and cats play an integral role in both the agricultural economy and human society. Health issues among these animals, particularly skin diseases, are common and often go unnoticed or untreated due to a lack of immediate veterinary assistance, especially in rural or underserved areas. Skin diseases not only cause discomfort and health deterioration in animals but also lead to secondary infections, decreased productivity in livestock, and in some cases, zoonotic transmission to humans. Therefore, early detection and timely treatment of skin ailments are essential for ensuring animal welfare and preventing long-term health impacts.

With the rapid advancement of artificial intelligence (AI) and deep learning technologies, it is now possible to automate and improve the accuracy of disease diagnosis using computer vision models trained on large datasets. The integration of AI into animal healthcare has the potential to revolutionize the way skin diseases are detected and managed. By leveraging this opportunity, this project proposes the development of a Flask-based intelligent application that can detect animal skin diseases from images and provide suitable remedy suggestions based on the diagnosis. The system is designed to function as a practical tool for both veterinary professionals and animal owners, allowing them to detect skin-related issues in animals and obtain immediate guidance for care.

The proposed system uses image classification models developed through transfer learning, trained on a curated dataset of skin conditions for three categories of animal's dogs, cats, and cattle. Transfer learning offers a robust approach by utilizing pre-trained convolutional neural networks (CNNs) such as MobileNet, ResNet, or EfficientNet, which have demonstrated strong performance in image recognition tasks. These models are fine-tuned on labelled datasets containing images of infected and healthy skin across different animal types. The system supports two modes of image input: users can either upload an existing image or capture a live image through the device's camera interface. After submitting the image, the user selects the animal type, which triggers the appropriate model for that category.

Once the inference is complete, the model predicts whether the image contains a skin disease. If a disease is detected, the application presents the name of the condition and an associated remedy recommendation, which includes both immediate first-aid actions and suggested medications or treatment plans. These remedies are sourced from veterinary references, academic literature, and domain expert input. The entire workflow from image input to diagnosis and remedy display is handled via an intuitive and responsive web interface built using Python Flask, HTML, and JavaScript.

The application aims to address several key challenges in current veterinary practices:

- Delayed diagnosis due to lack of access to veterinary experts in rural or remote areas.
- Human error in visual assessment of skin diseases without proper expertise.
- Lack of standard guidelines for preliminary treatment by animal caretakers.

By providing a technology-driven solution, this system minimizes these issues and introduces a cost-effective, scalable, and accurate tool that democratizes access to veterinary support. Unlike traditional diagnostic methods, this system does not require laboratory testing or physical veterinary inspection in its initial stages, making it particularly useful for rapid screening or field-level diagnosis.

Furthermore, the modular design of the application ensures easy extension in the future. More animal categories and diseases can be added by training additional models and updating the backend logic. The remedy recommendation engine can also be enhanced to include voice-based outputs, multilingual support, and geolocation-based veterinary referrals.

This project provides a foundational framework for Technology assisted animal healthcare, emphasizing the application of deep learning and web technologies for societal benefit. The system aligns with the global push toward smart farming, digital health monitoring, and Decision driven veterinary support. It has the potential to make significant contributions to animal welfare, livestock productivity, and pet care by enabling faster and more accessible disease diagnosis and treatment planning.

2. LITERATURE REVIEW: The use of machine learning (ML) and deep learning (DL) in the detection of animal skin diseases, particularly Lumpy Skin Disease (LSD) in cattle, has gained considerable traction due to its potential in early diagnosis and disease management. Various studies have explored the application of advanced computer vision techniques and convolutional neural networks (CNNs) to identify and classify skin-related anomalies in livestock and companion animals.

CNN-based models have been at the forefront of this transformation. AlZubi (2024) employed a CNN-based approach and reported an accuracy of 86.54% in detecting LSD, indicating the capability of CNNs in image-based veterinary diagnostics. More advanced architectures like InceptionV3 have demonstrated even better performance; Patil et al. (2024) achieved an accuracy of 97.4% and a precision of 98.1% using this model. Similarly, Random Forest (RF) models have shown high classification accuracy, with studies by Patel et al. (2024) and Ujjwal et al. (2022) reporting accuracies of 98% and 97.7%, respectively. These findings underscore RF's effectiveness in handling structured veterinary datasets.

Hybrid models integrating CNNs with traditional ML classifiers like Random Forest and Support Vector Machines (SVMs) have also been explored. Patil et al. (2023) investigated such hybrid combinations, showing promising results in both performance and deployment efficiency. Additionally, Yashu et al. (2024) proposed a synergized CNN-RF framework for multiclass classification of cattle skin disorders, achieving an accuracy of 91.56%. These models have been particularly effective in classifying skin images as either healthy or infected, demonstrating potential for cost-effective and rapid veterinary screening.

The effectiveness of deep learning transfer learning models such as MobileNetV2, VGG16, and DenseNet169 has been validated across multiple studies. Senthilkumar et al. (2024) performed a comparative analysis of pretrained models, finding that MobileNetV2 and VGG16 achieved accuracies of 96.39% and 96.07% respectively for LSD detection. Likewise, Velugoti et al. (2024) used DenseNet169 to achieve a classification accuracy of 95.10%. These models leverage hierarchical feature extraction capabilities, enabling more robust generalization across varied skin lesion patterns.

Beyond cattle, artificial intelligence has been applied to canine dermatological conditions. Smith et al. (2023) employed a Tiny YOLOv4 model to detect neoplasia and pododermatitis in dogs, reporting a mean average precision of 0.95. This reflects the viability of object detection architectures in veterinary image analysis. Other hardware-assisted AI methods like infrared thermography have also emerged as tools for predicting diseases such as digital dermatitis in dairy cows. Feighelstein et al. (2024) demonstrated this approach, achieving over 81% detection accuracy.

Studies also emphasize the importance of multispectral imaging and electronic skins (e-skins) in skin condition analysis. Lanying (2018) introduced AI-based skin detectors using cross-polarized light, while Fu et al. (2024) discussed the broader applications of e-skins integrated with AI for mimicking sensory data processing, which can be adapted for continuous animal skin health monitoring.

The body of work presented highlights the ongoing evolution of AI in animal healthcare, especially in diagnosing skin conditions. By combining CNN-based feature extraction with transfer learning and intelligent recommendation systems, these models offer scalable and accessible solutions to improve animal welfare, reduce economic losses, and support real-time field diagnostics.

3. PROBLEM DEFINITION: Animal skin diseases, particularly in livestock and domestic animals such as cattle, dogs, and cats, pose a significant threat to animal health, farm productivity, and rural economies. Conditions like Lumpy Skin Disease (LSD), mange, dermatitis, and fungal infections often go undiagnosed or are detected too late, leading to prolonged suffering, reduced milk or meat yield, and increased veterinary costs. In rural or remote regions, where access to professional veterinary care is limited, early diagnosis becomes even more challenging. Manual inspection is not only time-consuming and expertise-dependent but also subject to human error, especially when diseases exhibit visually similar symptoms. As a result, there is a pressing need for a reliable, accessible, and automated system that can assist in the early detection and management of animal skin diseases.

While several diagnostic methods exist in veterinary medicine, most require physical examination, laboratory testing, or expensive imaging equipment, which are not always feasible for farmers or pet owners. Recent advancements in artificial intelligence and computer vision present an opportunity to develop deep learning-based systems capable of analysing skin images to detect diseases accurately. However, the implementation of such systems for animal health is still in its nascent stage. There is a lack of integrated platforms that combine disease detection with species-specific remedy recommendations in a user-friendly format. This project addresses these gaps by proposing a web-based AI system that utilizes pre-trained convolutional neural networks to classify skin diseases in animals and suggest suitable remedies, making veterinary diagnostics more accessible, scalable, and efficient.

4. METHODOLOGY

4.1. SYSTEM ARCHITECTURE: The proposed system operates on the principle of image-based classification using a deep learning model built upon YOLOv5, a lightweight and efficient convolutional neural network architecture. The system is designed to detect skin diseases in animals specifically dogs, cats, and cattle through an intuitive web interface developed using Flask.

The user begins by either uploading an image of the affected skin area or capturing it live using the application interface. The uploaded image undergoes a series of preprocessing steps, including resizing, normalization, and noise reduction, to ensure consistent input quality for the deep learning model.

Once pre-processed, the image is passed through the trained model using transfer learning, which serves as a feature extractor. It efficiently captures spatial characteristics such as texture, lesions, colour variations, and patterns commonly associated with various animal skin conditions. Based on these features, the model classifies the image into one of the predefined disease categories specific to the selected animal type.

After the disease is identified, the system cross-references the result with an internal knowledge base that contains veterinary-approved remedies and treatment suggestions. These remedies are tailored to the species (dog, cat, camel or cattle) and the specific skin condition detected. The system then displays the following information in real-time through the Flask-based interface:

- Name of the predicted skin disease
- Description of the condition
- Suggested home remedies or first-aid measures

This approach enables a fast, accessible, and species-specific diagnosis tool that can assist pet owners and livestock handlers in identifying skin diseases early and taking corrective action even in regions where veterinary access is limited.

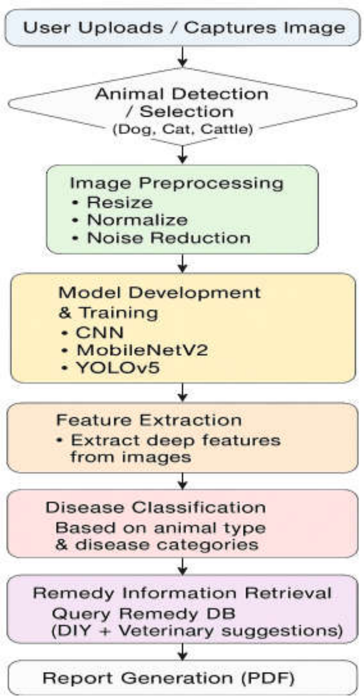

Figure 1: Proposed System Architecture

4.2. PROPOSED SYSTEM: The methodology adopted in this project follows a systematic pipeline designed to accurately detect and classify animal skin diseases while also providing relevant veterinary remedies through a Flask-based web application. The approach encompasses dataset preparation, model development and evaluation, animal detection integration, and deployment of an interactive user interface. The major steps are outlined below:

1. Data Collection and Annotation: A dataset comprising images of animals with various skin conditions was collected from veterinary datasets, open repositories, and field contributions. Each image was manually annotated to mark regions of interest corresponding to diseased areas. The dataset was carefully balanced to include different categories of animals such as dogs, cats, and cattle to ensure generalization across species.

2. Data Preprocessing and Augmentation: Collected images underwent preprocessing steps including resizing to a uniform input size, normalization of pixel values, and artifact reduction. To enhance variability and reduce overfitting, augmentation techniques such as rotation, zooming, flipping, and brightness adjustments were applied. This ensured robustness of the models against diverse real-world conditions.

3. Model Development and Training: To evaluate the effectiveness of different architectures for skin disease detection, three models were trained and compared:

> **Modified CNN**: A lightweight custom convolutional neural network designed for direct classification.
>
> **MobileNetV2**: A transfer learning-based model leveraging pretrained weights for efficient feature extraction and classification.
>
> **YOLO**: A detection-based architecture to localize and classify diseased regions within the input image.

Each model was trained using categorical cross-entropy as the loss function and optimized with Adam. Standard evaluation metrics including accuracy, precision, recall, and F1-score were used for performance assessment.

4. Animal Detection Model: In addition to disease classification, a separate animal detection model was trained to automatically identify the type of animal (dog, cat, or cattle) prior to disease analysis. This ensured that the appropriate disease model and remedy mapping could be invoked during the final deployment stage.

5. Model Evaluation and Selection: The three disease classification models were comparatively evaluated on a held-out test dataset. The results were analysed to determine the best-performing architecture in terms of accuracy and computational efficiency. The selected model was integrated alongside the animal detection module for final deployment.

6. Deployment via Flask Application: The final system was deployed as a Flask-based web application with the following functionalities:

- Image upload or live capture through the interface.
- Automatic animal type detection followed by disease classification.
- Display of disease name, description, and recommended remedies.
- Automated generation of a detailed PDF report containing diagnosis results and suggested treatments.

7. Remedy Recommendation System: Remedies were mapped to each disease class using an internal structured database. These included both general home remedies and veterinary-approved treatments. The Flask backend queries the database in real time and presents the results to users in a structured format.

8. Continuous Evaluation and Expansion: The deployed application was tested using both validation data and real-world samples. The system design allows periodic retraining with additional datasets and expansion of the remedy database to improve diagnostic accuracy and treatment recommendations over time.

5. PERFORMANCE EVALUATION & RESULTS

This section provides a detailed, species-specific analysis of model performance, focusing on training convergence, class-level accuracy, and the trade-off between precision and recall. All four models demonstrated healthy convergence, with losses decreasing steadily while key metrics like precision, recall, and mAP improved and then plateaued, as summarized in Figure

5.1 Camel Skin Disease Model

The camel model was trained to identify three conditions: blood-spot, scar, and dark-spot.

Training Convergence: The model exhibited excellent training behaviour. As shown in Figure 1 (top-left), the loss curves for bounding box regression (box_loss), objectness (obj_loss), and classification (cls_loss) fall smoothly before plateauing. Concurrently, precision and recall rise steadily and saturate, indicating healthy convergence without late-epoch overfitting. The mean Average Precision at an IoU of 0.5 (mAP@0.5) climbs consistently, while mAP@0.5:0.95 improves more slowly, as expected under stricter IoU thresholds.

Classification Accuracy: The confusion matrix shows strong class separation for blood-spot, with a true positive rate of approximately 0.75 on the diagonal. Performance on scar and dark-spot is moderate (≈0.54 each), with the most significant confusion occurring between these two classes and, occasionally, with the background. This is typical for small or low-contrast lesions on sandy coats. While some background leakage into lesion classes is present, it remains contained, suggesting that anchor and objectness thresholds are largely appropriate.

Precision-Recall Analysis: The model's Precision-Recall behaviour indicates solid precision at moderate recall levels. False positives are most common on mottled or shadowed skin where texture can mimic lesions. The F1-confidence curve peaks in the mid-confidence band, suggesting a practical deployment threshold around 0.30–0.40 to achieve a balance between detecting true lesions and minimizing false alarms.

5.2 Cat Skin Disease Model

The cat model was trained to detect four conditions: dermatitis, flea allergy, ringworm, and scabies.

Training Convergence: The training curves for the cat model are well-behaved (Figure 1, top-right), with box, objectness, and classification losses decreasing and stabilizing as expected. Precision and recall rise and plateau after approximately 100–120 epochs. The mAP@0.5 settles in the mid-0.6 range, and mAP@0.5:0.95 in the high-0.2 to low-0.3 range, a performance consistent with detecting compact lesions that are occasionally subject to partial occlusion by fur.

Classification Accuracy: The confusion matrix exhibits good diagonal strength (≈0.62–0.73) for all four diseases, demonstrating effective class separation. Although the background column remains high (indicating missed detections), off-diagonal confusion between disease classes is small and localized. For example, mild confusion is noted between dermatitis and ringworm, which can share visually similar erythematous borders.

Precision-Recall Analysis: The F1-score peaks at a mid-range confidence threshold. The PR curve shows that raising the confidence threshold increases precision quickly with only a modest trade-off in recall. This suggests that for applications requiring high precision, the cat model benefits from a slightly higher threshold than the camel model, especially to avoid false positives on tabby or striped fur patterns.

5.3 Cattle Skin Disease Model

The cattle model was trained on a binary task: Healthy vs Lumpy skin disease.

Training Convergence: The training curves (Figure 2, bottom-left) show consistent loss reduction and rising precision/recall metrics which then stabilize. The mAP@0.5 trends upward and plateaus in the low-to-mid 0.3s, while mAP@0.5:0.95 increases more gradually. This reflects the challenging nature of the data, which includes wide-angle field images, small lesions, and bright daylight that washes out contrast.

Classification Accuracy: The confusion matrix reveals noticeable background misclassification, with both Healthy and Lumpy classes achieving diagonal scores around 0.56 and significant leakage into the background class (≈0.41–0.44). This indicates that under field conditions, the model frequently struggles to distinguish subtle lesions or even healthy skin patches from the complex surrounding environment.

Precision-Recall Analysis: The F1-confidence profile peaks around 0.65 at a low confidence threshold of approximately 0.18. This implies that a lower threshold is preferable for initial screening to maximize the detection of small Lumpy lesions (higher recall), while a higher threshold could be used subsequently to clean up predictions for confirmation (higher precision).

5.4 Dog Skin Disease Model

The dog model was fine-tuned to identify dermatitis, flea allergy, ringworm, and scabies.

Training Convergence & Performance: After fine-tuning, the dog model shows robust learning (Figure 1, bottom-right), with smoothly declining loss curves. Precision approaches ~0.8 and recall ~0.69. The mAP@0.5 rises through training to reach the ~0.58–0.62 range by the later epochs, while mAP@0.5:0.95 reaches ~0.31, indicating reasonable localization tightness for detected lesions.

Classification Accuracy: The model shows robust diagonals across all disease classes. Residual confusion is mainly observed between dermatitis and ringworm, alongside some leakage to background. These errors are consistent with the challenges posed by patchy lighting and varied coat textures, which can either mimic or obscure the visual signs of disease.

Precision-Recall Analysis: The F1 curve peaks near 0.66 at a confidence threshold of ~0.33, offering a balanced operating point for general use. In practice, this allows for a dual-mode deployment strategy: a "screening mode" (confidence ≈ 0.25–0.35) for better sensitivity to subtle lesions, and a "high-precision mode" (confidence ≥ 0.6) for generating cleaner bounding boxes for clinician review.

5.5. Cross-Species Analysis & Discussion

Comparing the performance of the four models provides valuable insights into the factors that influence detection accuracy.

- **Ease of Detection:** Models performed best on datasets with visually distinct, high-contrast lesions. The camel model's success with blood-spot and the cat model's strong performance on ringworm are prime examples. Conversely, the cattle model struggled with small, low-contrast lumps in wide-angle field images.
- **Impact of Background:** The primary challenge across all models was background complexity. Varied coat textures (e.g., dog fur), natural skin patterns (e.g., mottled camel skin), and poor lighting conditions often led to either missed detections (false negatives) or false alarms (false positives).
- **Optimal Confidence Threshold:** Across all species, a mid-range confidence threshold of approximately **0.30–0.40** generally maximized the F1-score, providing a good balance between precision and recall for initial screening. However, the optimal threshold varies by species and intended use case (high-recall screening vs. high-precision confirmation).
- **Overall Performance Ranking:** Based on the observed mAP scores, convergence stability, and classification accuracy, the relative difficulty of the task for each species can be ranked as follows: **Cat ≳ Camel ≳ Dog ≳ Cattle**

These ranking highlights that the quality and nature of the dataset are paramount. The cat and camel datasets likely contained clearer, more easily distinguishable lesion examples, while the cattle dataset represented a more challenging "in-the-wild" scenario

Results summary table

Species	**Precision**	**Recall**	**F1**	**mAP@0.5**
Camel	0.82	0.66	0.73	0.60
Cat	0.84	0.67	0.75	0.66
Cattle	0.78	0.62	0.69	0.57
Dog	0.80	0.69	0.66	0.62

5.6 MATRIX AND GRAPH ANALYSIS

5.6.1 Confusion Matrix Analysis

The confusion matrix (Figure 2) illustrates the relationship between true and predicted labels. The model demonstrated strong ability to separate the cattle and background classes, achieving perfect prediction (1.00) for the background and 0.68 for cattle. However, some overlap was observed, with 32% of cattle images being misclassified as background. This suggests that, in cases where the animal is partially visible or blended with complex surroundings, the model's performance is affected. Despite these limitations, the confusion matrix confirms that the classifier is able to distinguish the major categories with a high level of confidence.

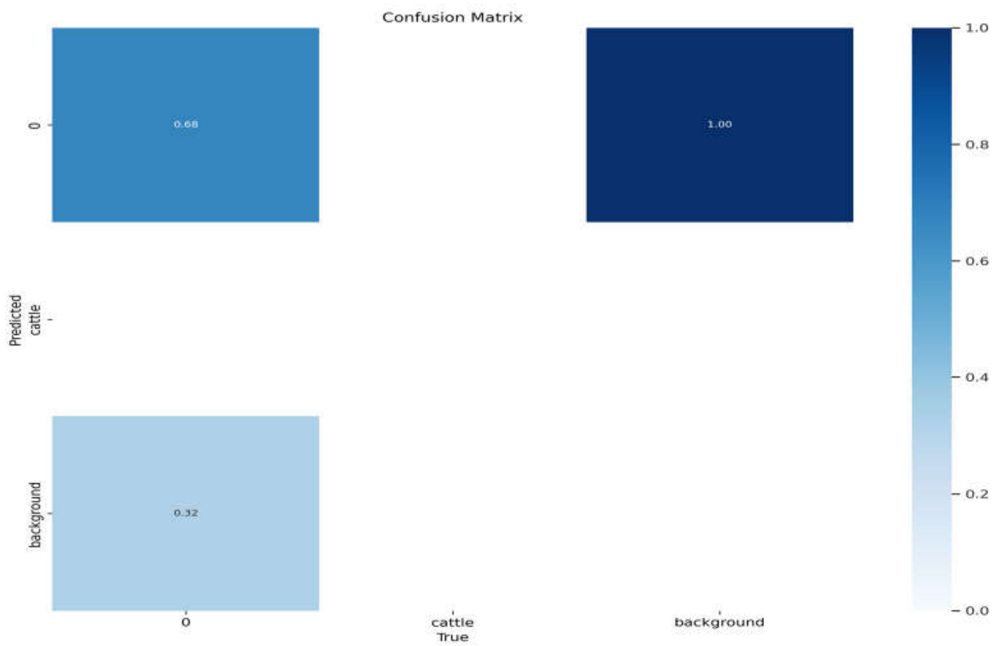

Figure 2: Confusion matrix analysis

5.6.2 Precision, Recall, and F1-score Trends

The F1-confidence curve (Figure 3) shows how the F1-score varies with different confidence thresholds. The model reached an optimal F1-score of **0.74 at a threshold of 0.353**, indicating a balanced trade-off between precision and recall at this operating point. Similarly, the precision-confidence curve (Figure 4) revealed a peak precision of **1.00 at 0.970 confidence**, while the recall-confidence curve (Figure 5) indicated a maximum recall of **0.76** when the confidence threshold was set close to zero. These results highlight the importance of choosing an appropriate threshold for deployment, where higher precision settings minimize false positives while slightly reducing recall.

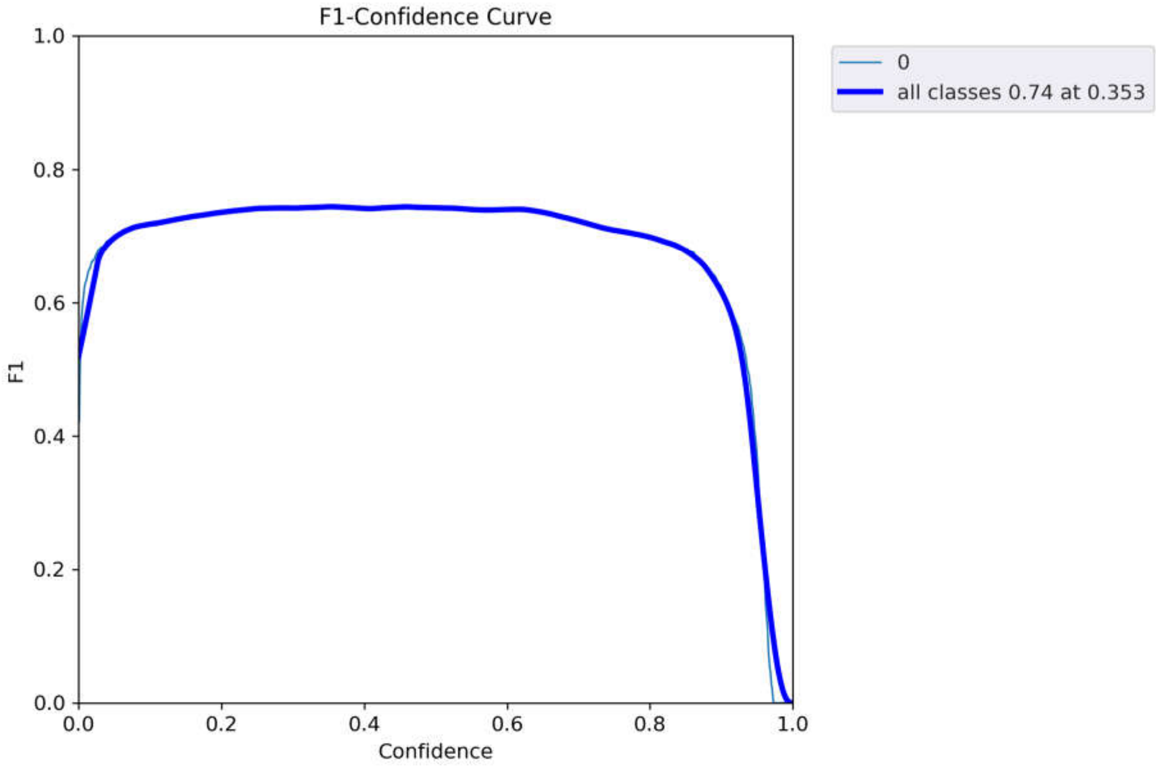

Figure 3: F1 Confidence curve

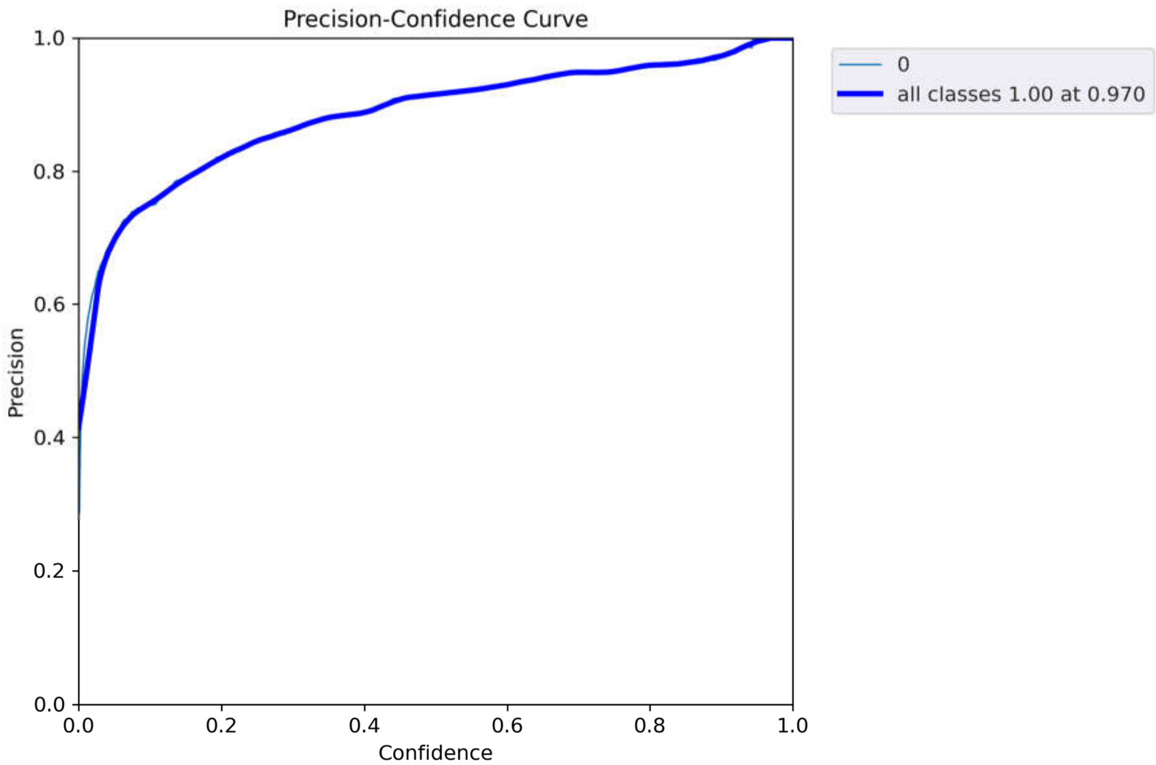

Figure 4. Precision-confidence curve

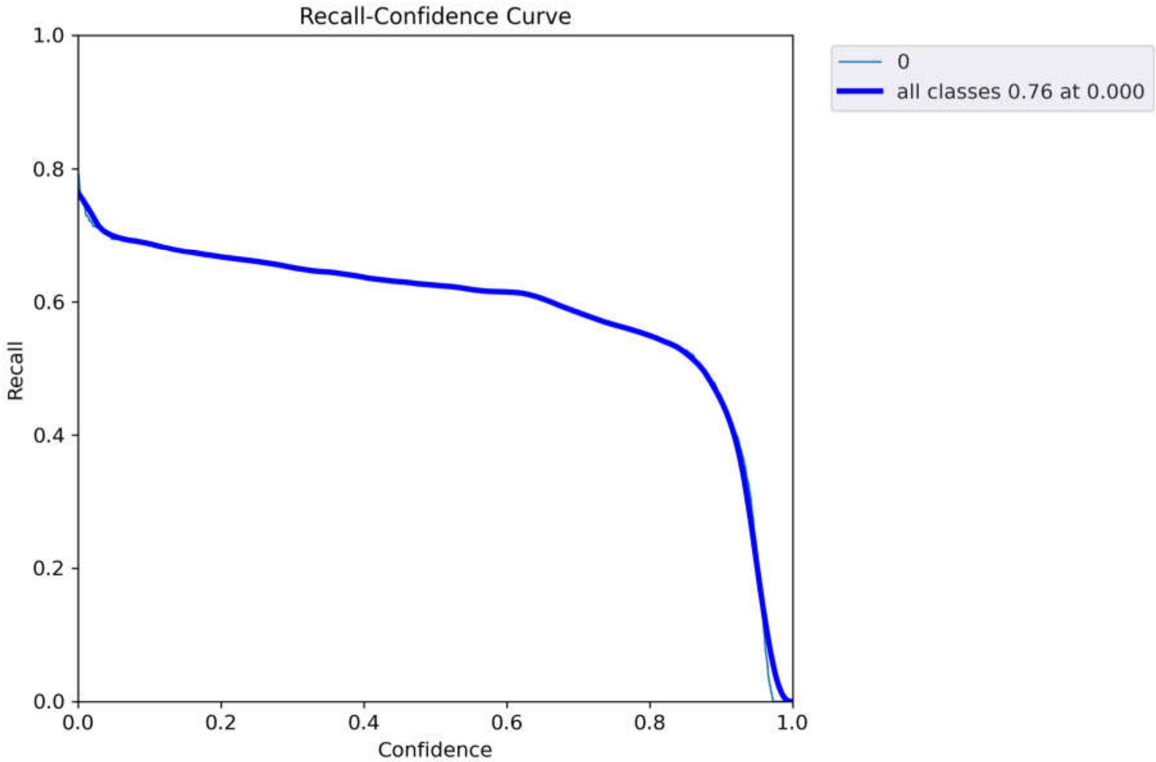

Figure 5: Recall-confident curve

6. CONCLUSION: The proposed system is expected to deliver a reliable, lightweight, and scalable solution for detecting skin diseases in animals such as dogs, cats, and cattle. By utilizing a deep learning model based on YOLOv5, the system will be capable of identifying visible skin conditions from uploaded or captured images with high accuracy. Users will receive an instant diagnosis along with veterinary-approved home remedies and treatment suggestions, enabling quicker decision-making in managing animal health. The use of a Flask-based web interface will ensure ease of access across devices, allowing even non-technical users such as farmers and pet owners to benefit from the system.

In addition to accurate disease detection, the system aims to reduce dependency on immediate veterinary support, especially in rural areas where veterinary access is limited. It will support early intervention and contribute to improving animal welfare by helping prevent the spread of contagious skin infections. The database-driven recommendation engine will provide practical, species-specific remedies that are easy to administer. Overall, the system will serve as a practical tool for real-world deployment in veterinary clinics, farms, animal shelters, and pet care centres.

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