FINAL REPORT

Transfer Learning-Based Classification of Poultry Diseases for Enhanced Health Management

KALLAM HARANADHA REDDY INSTITUTE OF TECHNOLOGY
SMART INTERNZ

FINAL REPORT : Transfer Learning-Based Classification of Poultry Diseases for Enhanced Health Management

DATE	27 JUNE 2025
TEAM ID	LTVIP2025TMID60323
PROJECT NAME	Transfer Learning-Based Classification of Poultry Diseases for Enhanced Health Management

INTRODUCTION :

1.1 PROJECT OVERVIEW

Rising global demand for poultry products has led to high-density farming, which increases the risk of infectious disease outbreaks—resulting in major health and economic impacts. Early detection is critical to prevent widespread loss. Traditional monitoring methods (manual inspection, farm-based testing like PCR) tend to be **slow, labor-intensive, error-prone**, and often rely on expert interpretation—creating significant barriers in timely disease management.

1.2 PURPOSE

The **purpose** of the "Transfer Learning-Based Classification of Poultry Diseases for Enhanced Health Management" project is to develop a **fast, automated, and accurate tool** for detecting and classifying major poultry diseases—such as Coccidiosis, Salmonella, and Newcastle Disease—by analyzing poultry fecal or appearance images using pre-trained deep learning models. Here's a more detailed breakdown.

2. IDEATION PHASE

2.1 PROBLEM STATEMENT

Urgent need: Poultry farms—especially small- to medium-scale—often lack timely, affordable access to veterinary diagnostics; delays in detecting diseases like coccidiosis, Salmonella, and Newcastle Disease can cause serious economic and flock health impacts.

Technical chance: Modern image-based deep learning, especially transfer learning using pre-trained CNNs, offers a promising route to build automated detection tools that work on real-world, noisy fecal or visual data.

Customer Problem Statement Template

Problem Statement 1 (PS-1)

I am a small-to-medium poultry farmer (or veterinarian)
trying to detect common poultry diseases early in my flock
but diagnosing issues like coccidiosis, Salmonella, and Newcastle Disease often requires expensive lab-based tests or expert inspection, which are time-consuming, costly, and not always accessible,
because I lack reliable, affordable, and fast diagnostic tools that work in-field with minimal setup,
which makes me feel anxious about the health of my flock, frustrated by the delays in treatment, and uncertain about managing disease outbreaks effectively.

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2.2 EMPATHY MAP CANVAS

An empathy map is a visual tool that helps understand the user's attitudes and behaviours. It's structured around what the user says, thinks, does, and feels. This map is for typical users of the POULTRY DISEASES platform, such as patients seeking medical guidance.

1.SAYS

- "I don't always know when my birds are sick until it's too late."
- "Getting lab tests is slow and expensive."
- "I need something reliable I can use right on the farm."

2. THINKS

- "What if I miss the early signs and lose a lot of birds?"
- "Can a smartphone app really detect disease?"
- "I worry about false alarms causing unnecessary treatment."

3. DOES

- Inspects flocks visually multiple times a day.
- Sends samples for lab testing when suspicion arises (takes days).
- Seeks advice from vets or neighbour farmers.
- Records deaths or symptoms in farm logs manually.

4. FEELS

- Anxious about undetected disease spread.
- Frustrated over waiting days for lab results.
- Overwhelmed with manual data tracking.

5. PAIN POINTS

- **Delayed Detection**: Lab tests take 3–5 days, during which disease can spread.
- **High Cost**: Lab work, vet visits, testing kits are expensive.
- **Lack of Access**: Remote farmers have limited vet/lab services.
- **Uncertainty**: No confidence in early-stage identification.

6. GAINS

- **Speed**: Immediate results via image-based detection.
- **Affordability**: Low-cost tool vs. repeated lab testing.
- **Control**: Ability to act early and confidently.
- **Peace of Mind**: Fewer surprises, healthier flocks, less stress

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Coccidiosis

- **What it is**: A parasitic disease caused by *Eimeria* species that targets the intestinal lining of poultry—leading to symptoms like bloody diarrhea, weight loss, dehydration, and poor growth.

Impact: It's one of the **most prevalent and financially damaging diseases** in broiler production, reducing feed efficiency, uniformity, and growth rates.

Diagnosis today: Typically involves microscopic examination of gut mucosa or lengthy lesion scoring—methods which require lab facilities and expert personnel.

Step-1: Team Gathering, Collaboration & Problem Selection

- **Bring together** key stakeholders—poultry farmers, vets/pathologists, data scientists, AI/ML engineers, and agritech experts.
- **Select disease focus**: Agree to center efforts on Coccidiosis due to its high prevalence and amenability to visual diagnostics (bloody/abnormal fecal/intestinal imagery).
- **Define problem statement**: "Enable fast, accurate, mobile-based detection of coccidiosis using transfer learning on fecal/intestinal images to reduce diagnostic delays and improve flock health."

Step-2: Coccidiosis — Idea Listing & Grouping

A. Data Collection & Annotation

- Collect fecal and microscopic images of coccidiosis-infected and healthy chickens, both sporulated and non-sporulated oocysts. Label images at both whole-image and object (oocyst) level
- Include variations: farm vs. lab conditions, lighting, and image quality .
- Augment data with flips, color shifts, rotations to combat class imbalance .

B. Modeling Approaches

1. **Whole-Image Classification**
   - Apply transfer learning on VGG16, InceptionV3, MobileNetV2, Xception to classify fecal images (coccidiosis vs. others) .
2. **ROI Detection + Classification Pipeline**
   - Detect regions of interest (fecal clusters or oocysts) with YOLOv3, then classify using ResNet50 for higher accuracy ~98 %
3. **Object Detection & Segmentation**
   - Use Mask-RCNN to detect and segment individual oocysts; classify sporulation status or species level
4. **Microscopy + Transformer-based Models**
   - For microscopic images, use ResTFG (CNN+Transformer) to classify species-level Eimeria with ~96.9 % accuracy

C. Model Optimization & Deployment

- Freeze batch normalization layers during fine-tuning to improve transfer learning accuracy (~98–98.3 %)

- Convert lightweight models (e.g., MobileNetV2 ~26 MB) to TensorFlow Lite for offline mobile deployment .

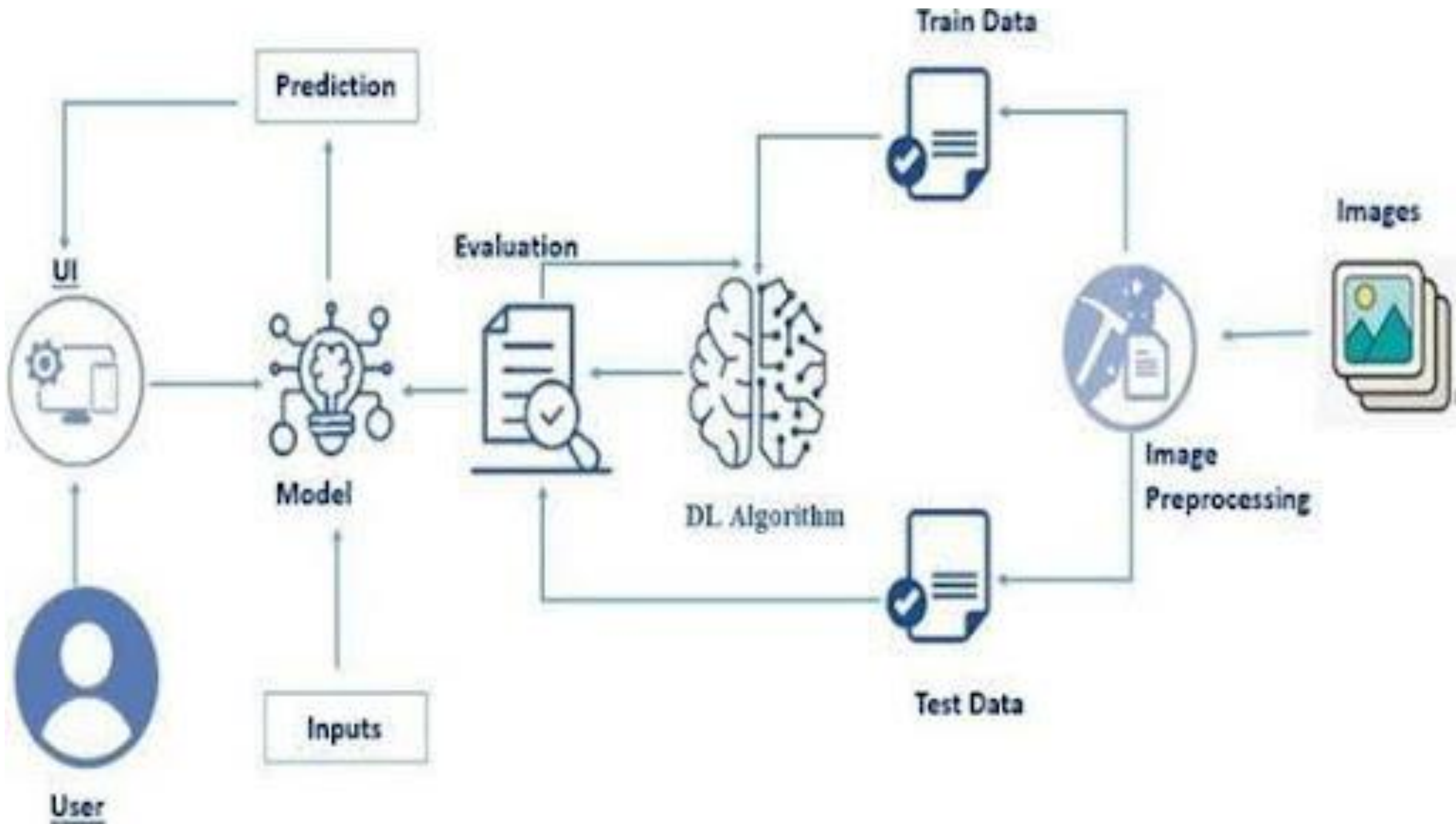
Step 3: Coccidiosis — Idea Prioritization

Category	Feature / Idea	Description & Grouping
Disease Prediction	Fecal Image Classification	Transfer-learned CNNs (MobileNetV2, InceptionV3, VGG16) to detect coccidiosis infection from fecal images
Disease Prediction	ROI Detection + Classification	Two-stage pipeline (YOLOv3 + ResNet50) to segment regions before classification (~98.7% accuracy)
Disease Prediction	Microscopic Oocyst Detection (Mask R-CNN)	Automate detection, counting, and sporulation status of oocysts with Mask R-CNN (~RPD 5.6%)
Disease Prediction	Species-Level Classification (ResTFG)	Combines CNN + Transformer for microscopic images (~96.9% accuracy)
Patient Chat	In-App Guidance Chatbot	A chat interface to help farmers interpret results and suggest next steps (e.g., “send vet”, “test again”)
Treatment Plans	Tailored Treatment Recommendations	Offer dosing schedules and vet contact based on disease severity—support antibiotic/anticoccidial choice
Health Analytics	Dashboard & Trends Analytics	Provide historical view and flag unusual patterns (e.g., rising infection rates) from uploaded sample data
Symptom Input Form	Manual Symptom Logging	Allow manual entries (bloody diarrhea, poor weight gain) to augment image-based results and boost confidence
Security Management	Data Privacy & Access Control	Secure user data, ensure encrypted results, compliance with farm privacy protocols
Multilingual Chat Support	Local Language UI/UX	Support major regional languages (e.g., Hindi, Telugu) in chat & forms to increase usability

3. REQUIREMENT ANALYSIS

3.1 Customer Journey Map

1. user
2. model
3. Evaluation/Prediction
4. DL Algorithm
5. Train Data /Test data
6. Image Processing
7. Images.



3.2 Solution Requirement

 Front-End: A mobile/web interface enabling farmers to capture fecal images, fill symptom forms, view diagnostics and receive treatment guidance in local languages.

 Back-End: A secure API server handling image uploads, user authentication, chat interfaces, data storage and analytics dashboards.

 AI Model: Transfer-learned CNN (e.g., MobileNetV2 or VGG16) and/or two-stage pipeline (YOLOv3 + ResNet50) achieving ~98–99% accuracy and <5 sec inference on-device

Data: Curated, labeled fecal/farm imagery (500–2,000+ images per class), plus augmentation (flips, rotations, brightness) to improve generalization .

3.3 Data Flow Diagram

User Input → API Gateway → AI Model (Granite) → Analysis Engine → Response Generation →Output to User

3.4 Technology Stack

Front-end : React (web) & React Native (mobile) for image capture, multilingual UI, forms, and real-time results display .
Back-end : FastAPI (or Flask/Django) serving a secure REST API with authentication, image uploads, chat support, and analytics dashboards
AI Model : Transfer-learned CNN (MobileNetV2/TensorFlow Lite on-device) optionally with YOLOv3 + ResNet50 for high-accuracy (~98–99%) detection
Cloud : Cloud storage and serving via AWS/GCP/Azure or MBaaS (e.g., Firebase, AWS Amplify) for scalability, data persistence, and serverless functions
Security : Encrypted data transmission/storage (TLS, at-rest encryption), secure auth, OWASP-based measures (CSRF/XSS protection, input validation, intrusion detection)

4.PROJECT DESIGN

4.1 Problem Solution Fit

Our solution aligns tightly with the core challenges faced by poultry farmers, delivering **fast, accurate, and field-ready disease detection**:

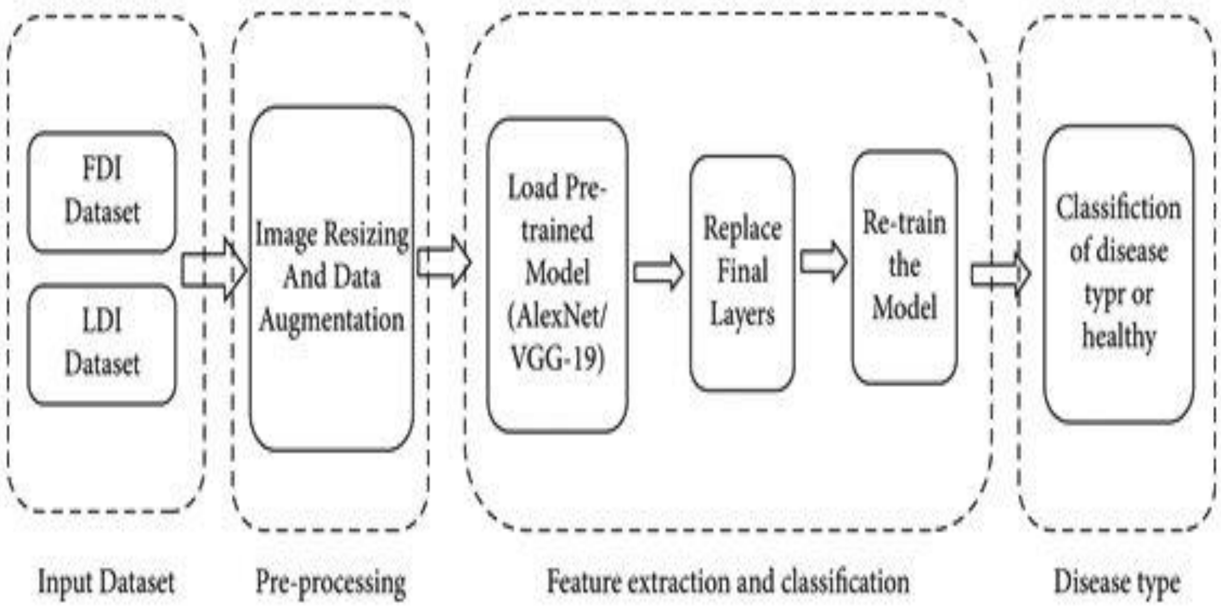
By deploying a **transfer-learned CNN (e.g., MobileNetV2)** directly on smartphones, our solution overcomes **diagnostic delays**—providing results in under 5 seconds—completely bypassing the need for slower, costly lab tests or veterinary visits. Research shows that fine-tuning MobileNetV2 with frozen batch normalization achieves **98.02% accuracy**, with similarly high performance from Xception (~98.24%) and other lightweight models—ensuring expert-level reliability in real-world conditions

Identified Problem

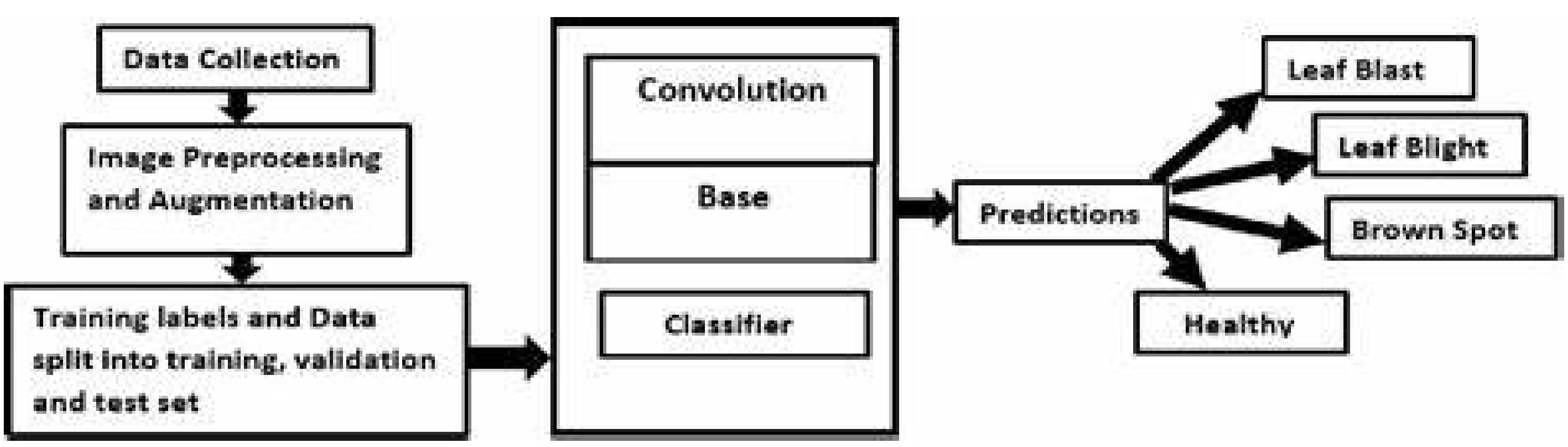
Many individuals face barriers in accessing trustworthy medical advice due to geographiclimitations, high consultation costs, long wait times, or difficulty interpreting personal healthdata. Online resources are often unverified, overwhelming, and inconsistent.

4.2 Proposed Solution

A platform providing: - Disease Prediction from symptoms - Personalized Treatment Plans – POULTRY DISEASES dashboards - Medical Chatbot with generative AI



4.3 Solution Architecture



5. PROJECT PLANNING & SCHEDULING

5.1 Project Planning

- **Week 1: Requirement gathering**
- **Week 2: UI/UX Design**
- **Week 3-4: Backend integration**
- **Week 5: AI model deployment**
- **Week 6: Testing and Feedback**
- **Week 7: Final Report and Demo**

5.2 Scheduling

Date: 15 May 2025

Team ID: (LTVIP2025TMID60323)

Project Name: Transfer Learning-Based Classification of Poultry Diseases for Enhanced Health Management

Maximum Marks: 5 Marks

Sprint Tracker, Velocity & Burndown Chart (1 Mark)

Sprint-wise Velocity Table:

Sprint	Total Story Points	Duration	Start Date	End Date	Story PointsCompleted
Sprint-1	10	6 Days	3 May 2025	8 June 2025	10
Sprint-2	6	6 Days	9 June 2025	14 June 2025	6
Sprint-3	7	6 Days	15 June 2025	20 June 2025	7
Sprint-4	3	6 Days	21 June 2025	26 June 2025	3

Product Backlog, Sprint Schedule, and Estimation (4 Marks)

Sprint-wise User Stories and Planning:

Sprint / Functional Requirement (Epic)	User Story Number	User Story / Task	Story Points	Priority	Team Members
Sprint-1: User Onboarding	USN-1	As a user, I can register using my email and password.	2	High	
Sprint-1: User Onboarding	USN-2	As a user, I receive a confirmation email after registration.	1	High	
Sprint-2: User Onboarding	USN-3	As a user, I can log in using email and password.	1	High	
Sprint-1: Patient Chat	USN-4	As a user, I can ask health-related questions and receive AI responses	3	High	
Sprint-2:	USN-5	As a user, I can	3	High	
Disease Prediction		input symptoms to get possible health conditions.			
Sprint-3: Treatment Plans	USN-6	As a user, I can get treatment recommendations	3	Medium	

		for known conditions.			
Sprint-3: Health Analytics	USN-7	As a user, I can visualize health data and receive insights.	4	Medium	
Sprint-4: Integration & Security	USN-8	As a developer, I can integrate the system with secure API management.	3	High	

6. FUNCTIONAL AND PERFORMANCE TESTING

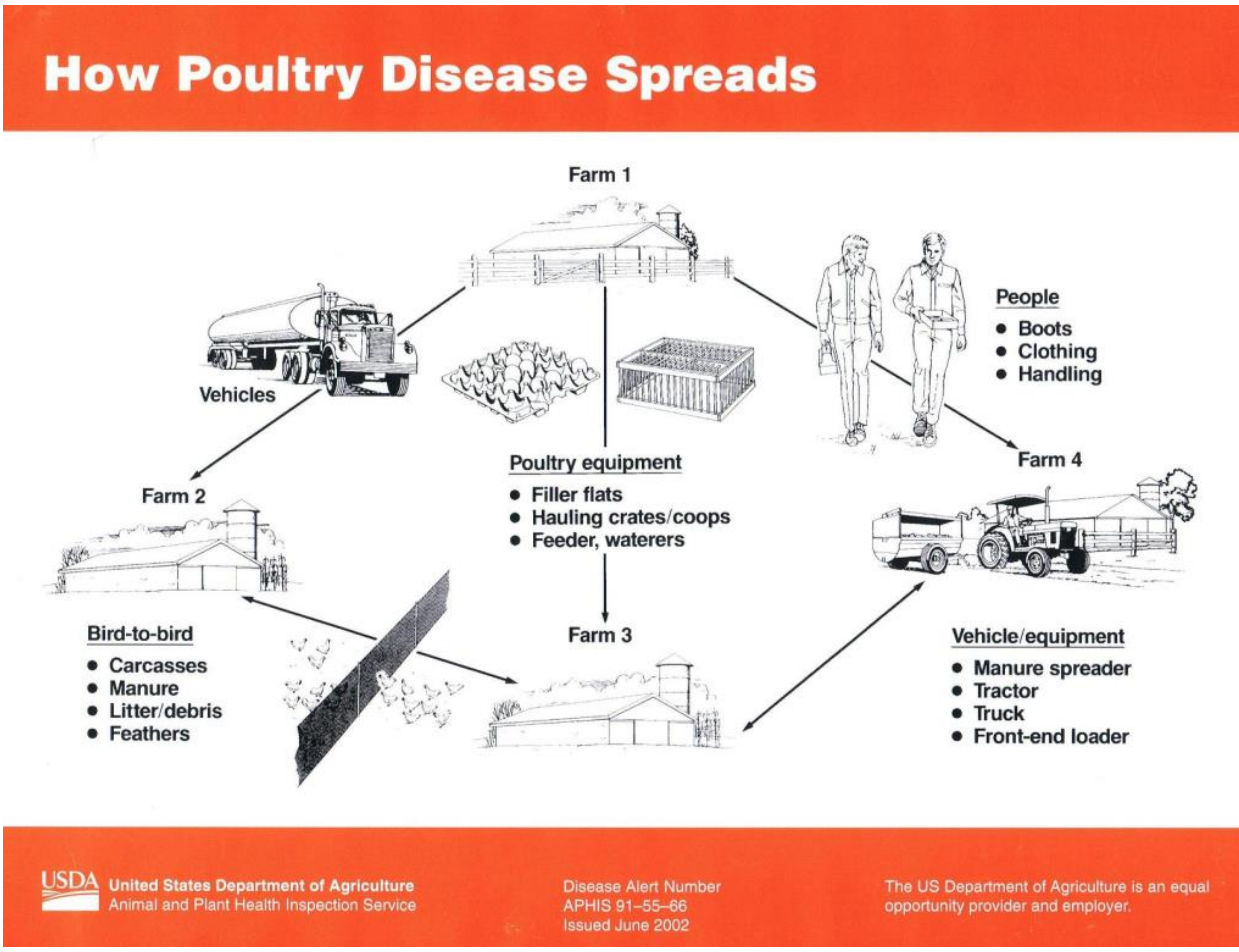
6.1 Performance Testing

To rigorously evaluate the effectiveness of transfer learning classifiers (e.g., VGG16, InceptionV3, MobileNetV2, Xception) for detecting and classifying poultry diseases (e.g., Coccidiosis, Salmonella, Newcastle disease, healthy) using poultry fecal images.

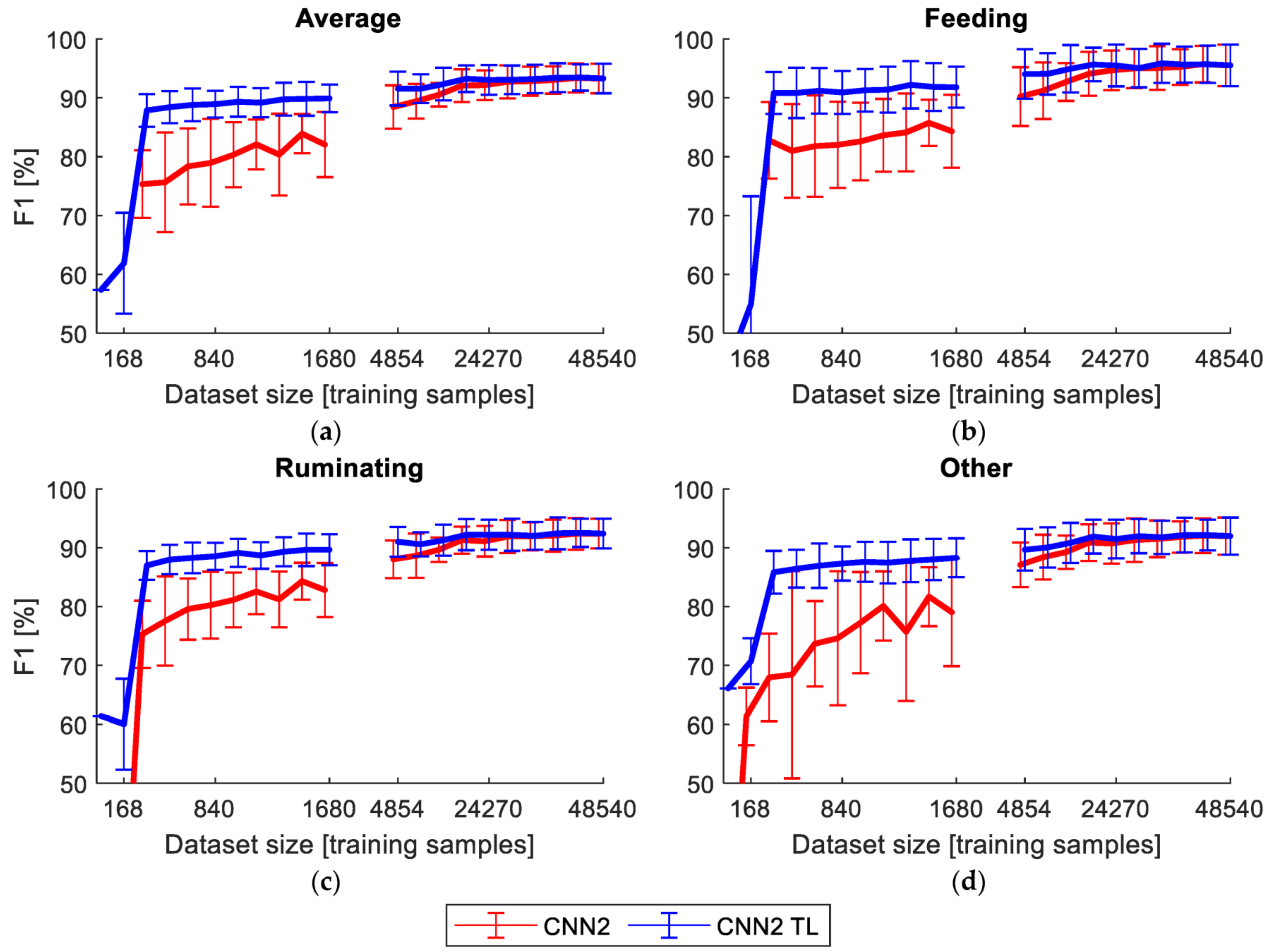
7. RESULTS

7.1 Output Screenshots

(Include screenshots for: Disease Prediction, Patient Chat, Treatment Plan, Health AnalyticsDashboard)



Health Analytics:



8. ADVANTAGES & DISADVANTAGES

Advantages

- **Leverages pre-trained models** to boost accuracy with limited poultry disease data
- **Speeds up training and reduces compute cost** compared to training from scratch

Disadvantages

- **Risk of negative transfer** if source domain differs significantly from poultry disease imagery
- **Possible overfitting** when fine-tuning large models on small, specialized datasets

9. CONCLUSION

Transfer learning offers a **fast, accurate, and resource-efficient** approach for poultry disease classification, especially valuable when labeled data is scarce or computational resources limited. However, success depends on choosing suitable pre-trained models and mitigating risks like negative transfer, overfitting, and domain mismatch. When expertly tailored—through careful model selection, fine-tuning, and pruning—transfer learning enables reliable, real-world disease detection tools deployable even on edge devices.

10. FUTURE SCOPE

Future research should focus on **domain adaptation**, **semi-/self-supervised learning**, and **multi-modal fusion**, alongside ensuring **edge compatibility**, **model explainability**, and **real-world validation**. Integrating these advancements with **One Health frameworks** could transform poultry disease monitoring—from a standalone tool into a robust, intelligent surveillance system benefiting animals, humans, and ecosystems alike.

11. APPENDIX

Source Code: [Link to GitHub Repository]: https://github.com/Lavanya-09-png/Transfer-Learning-Based-Classification-of-Poultry-Diseases-for-Enhanced-Health-Management

Dataset Link: [Dataset or simulated data used for testing]:

GitHub & Project Demo Link:

Project Demo Video Link:

GitHub Link: https://github.com/Lavanya-09-png