

Pawlytics: Pet Behavior and Health Analysis Using AI / ML

Guided By: Prof. A. S. Khaple

Assistant Professor, Computer Engineering

Zeal college of Engineering and Research, Pune, India.

Ghanashyam Ahire, Anuj Bankar, Soham Bende, Sanika Dharme

Undergraduate Student, Computer Engineering Zeal college of Engineering and Research, Pune, India

Abstract:

The increasing importance of companion animals in modern families has created a need for intelligent systems capable of monitoring their emotional and behavioural well-being. However, early detection of stress, discomfort, and health-related issues in pets remains difficult because animals cannot communicate their conditions directly. Existing pet-care applications primarily focus on activity tracking and record management, providing limited support for emotion recognition and proactive healthcare.

This paper presents Pawlytics, an AI/ML based pet healthcare system that performs image-based pet emotion recognition and behavioural analysis. The proposed framework employs a MobileNetV2 deep learning model implemented using PyTorch to classify pet emotions into four categories: Happy, Angry, Sad, and Relaxed. The trained model is integrated into a cross-platform mobile application that provides real-time emotion detection, behavioural insights, and personalized health recommendations.

By integrating emotion analysis and intelligent recommendations within a single platform, Pawlytics supports preventive pet healthcare and assists owners and veterinary professionals in making informed decisions. The proposed framework contributes toward improving pet wellness and promoting data-driven pet healthcare management.

Keywords: Artificial Intelligence, Machine Learning, MobileNetV2, Pet Emotion Recognition, Behaviour Analysis, Veterinary Healthcare, Computer Vision.

I. INTRODUCTION

The relationship between humans and companion animals has evolved significantly in recent years, with pets increasingly being regarded as integral members of modern families. Consequently, ensuring the physical and emotional well-being of companion animals has become an important concern for pet owners and veterinary professionals. Despite advancements in veterinary medicine, the early identification of behavioural abnormalities, emotional distress, and health-related issues remains challenging because animals cannot verbally communicate discomfort, stress, anxiety, or illness.

Traditional pet-care practices primarily rely on manual observation and periodic veterinary consultations. Such approaches are largely reactive and often fail to identify subtle changes in facial

expressions, activity patterns, and behavioural states during the early stages of illness or psychological distress. Delayed recognition of these indicators may result in increased treatment costs, reduced treatment effectiveness, and deterioration in the quality of life of companion animals.

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), and Computer Vision have enabled the development of intelligent systems capable of analysing images and behavioural patterns for healthcare applications. Several studies have explored emotion recognition and behaviour monitoring in animals; however, existing approaches are often limited by high computational requirements, species-specific implementations, or the lack of integrated healthcare support features. Furthermore, many available pet-care applications focus primarily on activity tracking and record management, providing limited support for real-time emotion analysis and proactive healthcare recommendations.

To address these limitations, this paper presents *Pawlytics*, an AI-driven pet behaviour and health analysis framework that combines image-based emotion recognition and behavioural analytics to support preventive pet healthcare. The proposed framework employs a lightweight deep learning model for multi-class pet emotion classification and integrates intelligent recommendations to assist pet owners in understanding the emotional and behavioural conditions of their pets.

II. OBJECTIVES

The primary objective of this research is to develop an Artificial Intelligence (AI) and Machine Learning (ML)-based framework for analysing the emotional and behavioural states of companion animals and supporting proactive pet healthcare through intelligent monitoring and recommendation mechanisms.

The specific objectives of the proposed work are as follows:

1. **Pet Emotion Recognition:** To develop a deep learning-based model capable of classifying pet emotions from images into four categories: Happy, Angry, Sad, and Relaxed.
2. **Behavioural Analysis and Health Monitoring:** To analyse behavioural patterns and identify abnormal activities that may indicate stress, discomfort, or potential health issues.
3. **Early Health Risk Identification:** To utilize AI and ML techniques for detecting behavioural abnormalities and assisting in the early identification of possible health concerns.
4. **Personalized Recommendation Generation:** To generate intelligent recommendations related to pet care, nutrition, physical activity, and veterinary consultation based on emotion and behavioural analysis.
5. **Veterinary Decision Support:** To generate structured reports containing behavioural observations and emotional trends that can assist veterinary professionals in diagnosis and treatment planning.
6. **Real-Time Mobile Deployment:** To implement a lightweight and efficient framework suitable for real-time deployment in a mobile application environment for practical pet healthcare management.

III. LITERATURE SURVEY

A. Review of Existing Research

Authors	Year	Methodology	Major Contribution	Limitation
V. Tanwar	2024	CNN-based emotion classification	Recognized dog emotions using facial expressions and posture features	Limited to dogs and restricted dataset diversity
M. Lee, J. Hernandez, and K. Park.	2023	Machine Learning-based behaviour monitoring	Detected behavioural changes associated with stress and illness	No emotion recognition and limited species support
A. Patel, R. Sharma, and P. Gupta	2022	SVM, Random Forest, Neural Networks	Predicted common pet diseases using ML techniques	Small and geographically constrained dataset
K. Johnson and M. Carter	2021	Predictive analytics models	Identified obesity and nutritional deficiencies in pets	Focused only on physical health analysis
X. Li, Y. Zhao, and H. Chen	2020	Computer Vision and image processing	Detected abnormal animal behaviours such as aggression and inactivity	Performance degradation under complex environments
H. Guo, Z. Liu, and Y. Zhang	2023	Multimodal Deep Learning	Combined visual and audio data for emotion recognition	High computational complexity and limited mobile deployment

The analysis of existing studies reveals several limitations:

- Most systems are limited to specific animal species and do not generalize well to multiple companion animals.
- Existing approaches often focus on either behaviour monitoring or disease prediction, with limited integration of emotion recognition and healthcare support.
- Several deep learning methods require significant computational resources, restricting real-time mobile deployment.
- Current pet-care applications primarily provide activity tracking and record management and lack intelligent recommendation and decision-support capabilities.
- Integrated frameworks combining emotion recognition, behavioural analytics, and personalized healthcare recommendations remain largely unexplored.

The identified limitations highlight the need for an intelligent, lightweight, and integrated pet healthcare framework capable of performing real-time emotion recognition and behavioural analysis while providing actionable insights for pet owners and veterinary professionals. Therefore, this research proposes *Pawlytics*, an AI-driven framework that combines image-based pet emotion recognition with behavioural analytics and recommendation mechanisms to support preventive and data-driven pet healthcare management.

IV. PROPOSED SYSTEM AND SYSTEM ARCHITECTURE

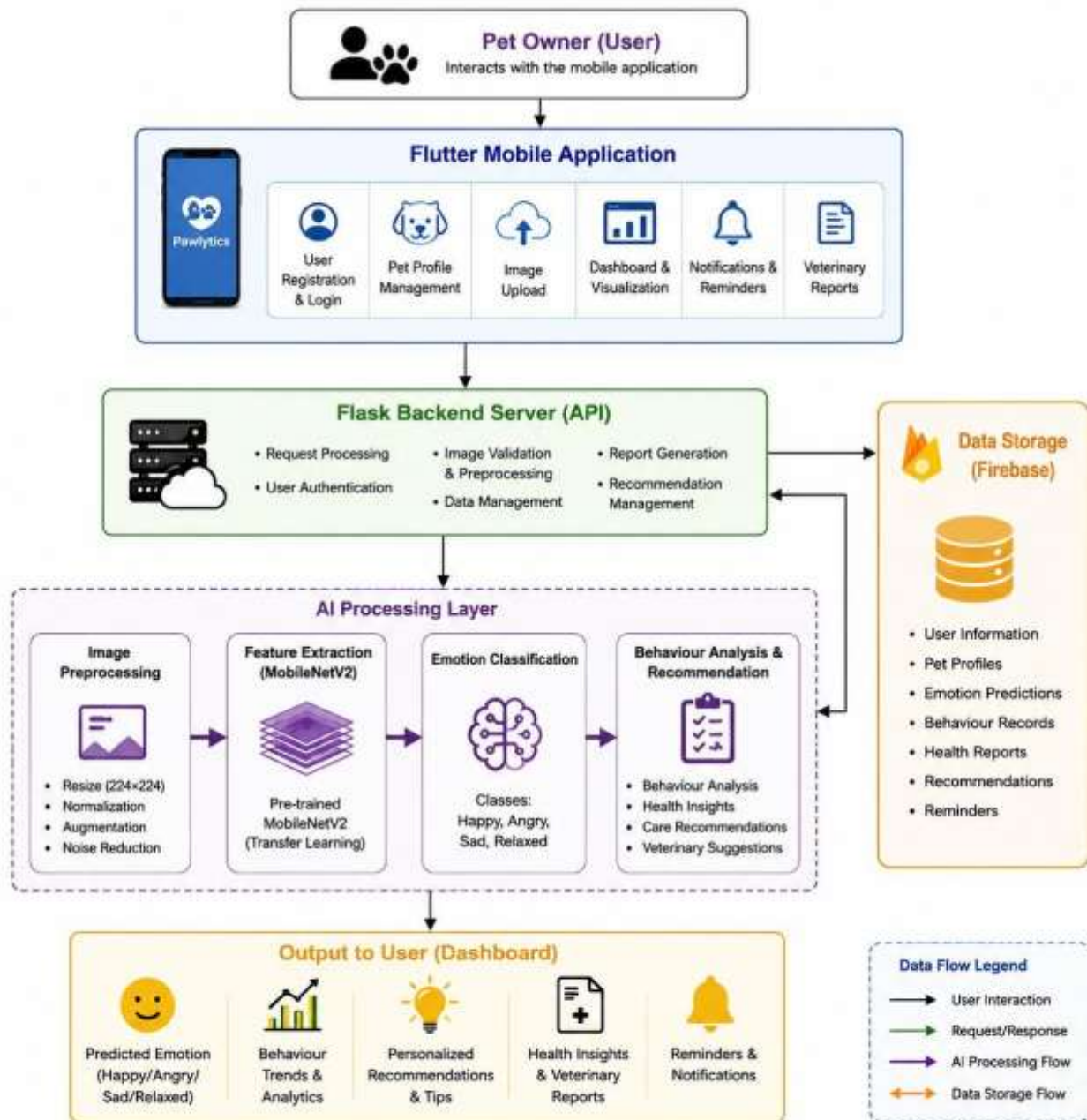


Figure 1. Proposed System Architecture of Pawlytics

Layer	Responsibility
Presentation Layer	User interaction and dashboard
Processing Layer	API communication and preprocessing
AI Layer	Feature extraction and emotion classification
Data Layer	Storage of predictions and reports

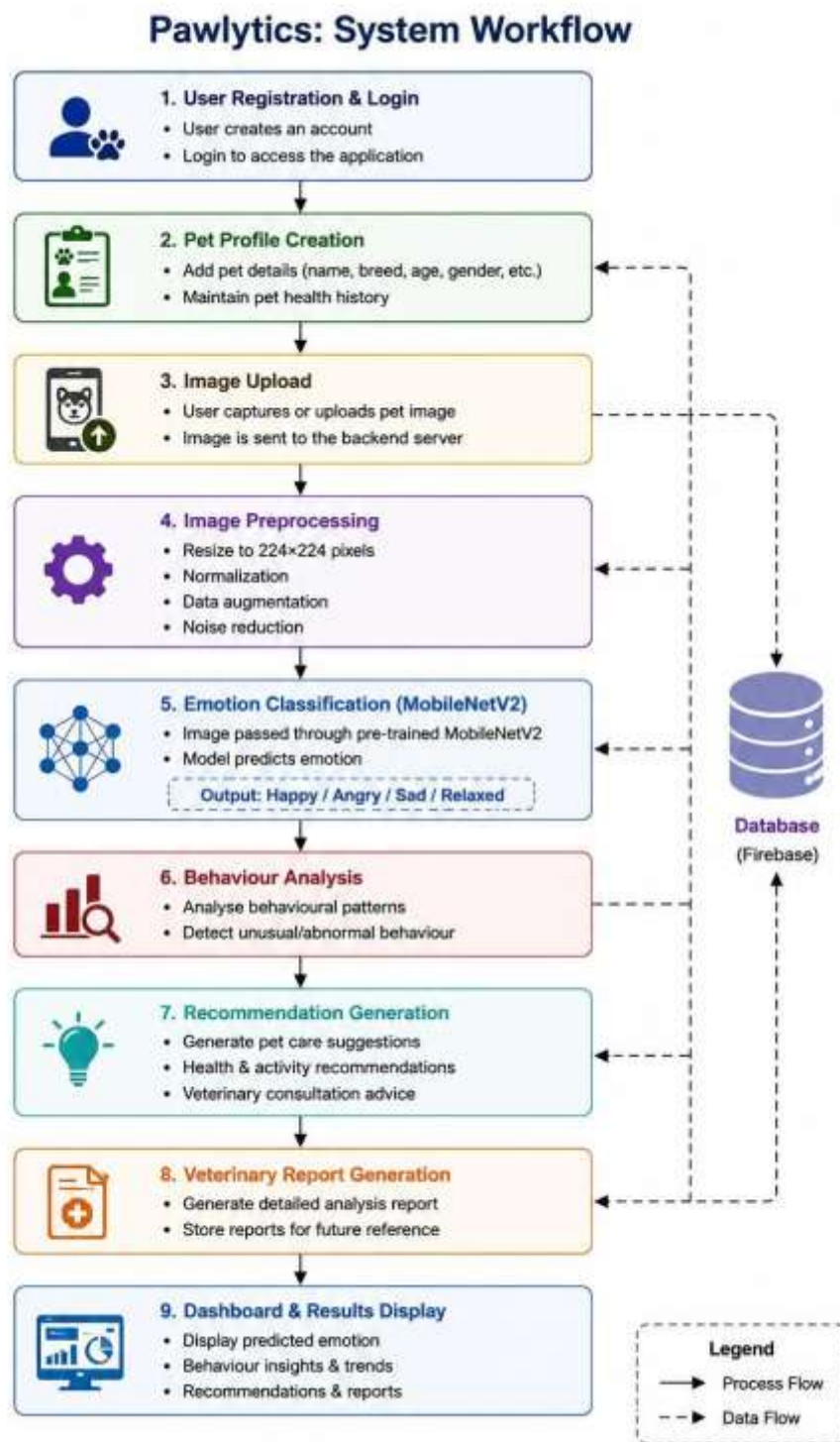


Figure 2. Workflow of the Proposed Pawlytics System

Working Principle of the Proposed System

The proposed Pawlytics framework follows a layered architecture consisting of the presentation layer, application processing layer, artificial intelligence layer, and data storage layer. The system begins with user interaction through a Flutter-based mobile application, where pet owners can create profiles and upload pet images. The uploaded images are transmitted to the backend server through secure API communication.

The backend performs preprocessing operations, including image resizing, normalization, and validation, before forwarding the processed images to the MobileNetV2-based emotion recognition model. The deep learning model extracts discriminative visual features and classifies the uploaded image into one of four emotional categories: Happy, Angry, Sad, or Relaxed.

The predicted emotional state is subsequently analysed by the recommendation engine, which combines the current prediction with historical behavioural records stored in the database. Based on this analysis, personalized recommendations, behavioural insights, and veterinary reports are generated and displayed through the application dashboard.

The layered architecture ensures modularity, scalability, and computational efficiency, making the proposed framework suitable for real-time mobile deployment and practical pet healthcare applications.

V. METHODOLOGY

The methodology consists of dataset preparation, image preprocessing, classification, model training, performance evaluation, and recommendation generation.

A. Dataset Collection

The dataset was divided into training, validation, and testing subsets using a 70:15:15 ratio, enabling effective model learning and unbiased performance evaluation. Images representing different breeds, age groups, and environmental conditions were included to improve diversity and reduce model bias.

The dataset was collected from publicly available repositories containing images captured under diverse environmental conditions, breeds, and behavioural states. Low-quality and incorrectly labelled images were removed during preprocessing.

B. Data Preprocessing

1. Image Resizing

All images were resized to 224×224 pixels to satisfy the input requirements

2. Normalization

Pixel values were normalized within the range:

$$0 \leq x_{\text{norm}} \leq 1 \text{ using } x_{\text{norm}} = X/255$$

where: X = original pixel intensity, x_{norm} = normalized pixel value

3. Data Augmentation

Augmentation techniques were applied Random Rotation, Horizontal Flipping, Random Cropping, Brightness Adjustment, Zoom Transformation

4. Noise Reduction

Low-quality and noisy images were filtered to improve feature extraction and reduce classification errors.

5. Label Encoding

The emotional categories were converted into numerical labels: Happy = 0, Angry = 1, Sad = 2, Relaxed = 3. After preprocessing, all images were converted into PyTorch tensors and prepared for model training.

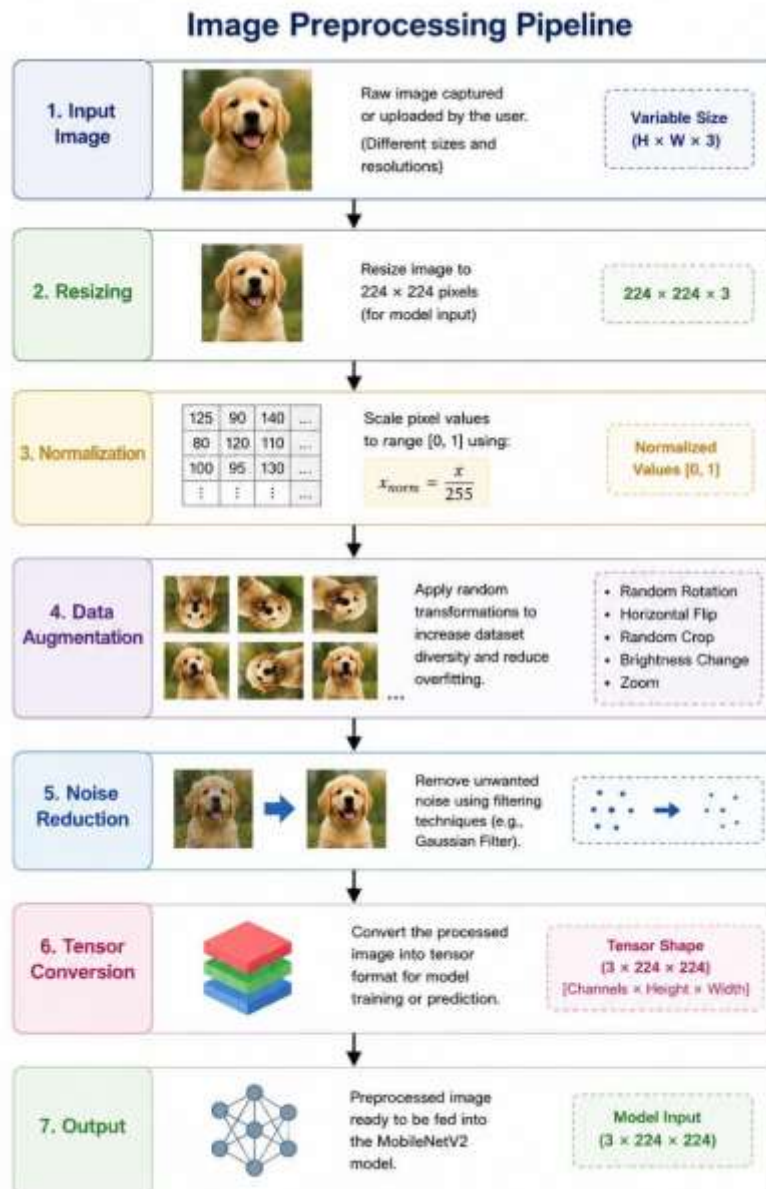


Figure 3. Image Preprocessing Pipeline

C. MobileNetV2 Architecture

The proposed framework employs MobileNetV2, a lightweight Convolutional Neural Network (CNN) architecture designed for mobile and embedded applications. MobileNetV2 uses depthwise separable convolutions and inverted residual bottleneck blocks, which significantly reduce computational cost while maintaining high classification performance.

Depthwise Convolution

The output of depthwise convolution is represented as:

$$Y(i, j, k) = \sum_m \sum_n K(m, n, k) \cdot X(i + m, j + n, k)$$

where: X = input feature map, K = convolution kernel, Y = output feature map

Pointwise Convolution

The pointwise convolution is defined as:

$$Y(i, j, c) = \sum_{k=1}^M W(k, c) \cdot X(i, j, k)$$

where: M = number of input channels, W = learnable weights

Transfer Learning

To improve classification accuracy and reduce training time, transfer learning was employed using an ImageNet-pretrained MobileNetV2 model. The convolutional layers were used as feature extractors, while the final fully connected layer was replaced by a four-class Softmax classifier.

Softmax Classification

The probability of each emotion class is calculated as:

$$P(y(i)) = \frac{e^{z(i)}}{\sum_{j=1}^C e^{z(j)}}$$

where: z(i) = output score of class (i), C = total number of classes

The predicted emotion corresponds to the class having the maximum probability.

D. Model Training Configuration

The MobileNetV2 model was implemented using the PyTorch framework and trained using supervised learning.

Training Parameters

Parameter	Value
Architecture	MobileNetV2
Framework	PyTorch
Classes	4
Input Size	224 × 224
Batch Size	32
Epochs	25
Learning Rate	0.001
Optimizer	Adam
Loss Function	Cross Entropy Loss

Cross Entropy Loss

The loss function is defined as:

$$L = - \sum_{i=1}^C y(i) \log(P(i))$$

where: C = number of classes, Y(i) = actual label, P(i) = predicted probability

The Adam optimizer was employed to update network parameters through backpropagation.

E. Performance Evaluation Metrics

The proposed framework was evaluated using Accuracy, Precision, Recall, and F1-Score.

Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision

$$Precision = \frac{TP}{TP + FP}$$

Recall

$$Recall = \frac{TP}{TP + FN}$$

F1-Score

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

where:

$$Precision \times Recall$$

TP = True Positives TN = True
Negatives

FP = False Positives FN = False Negatives

These metrics provide a comprehensive assessment of the classification performance of the proposed framework.

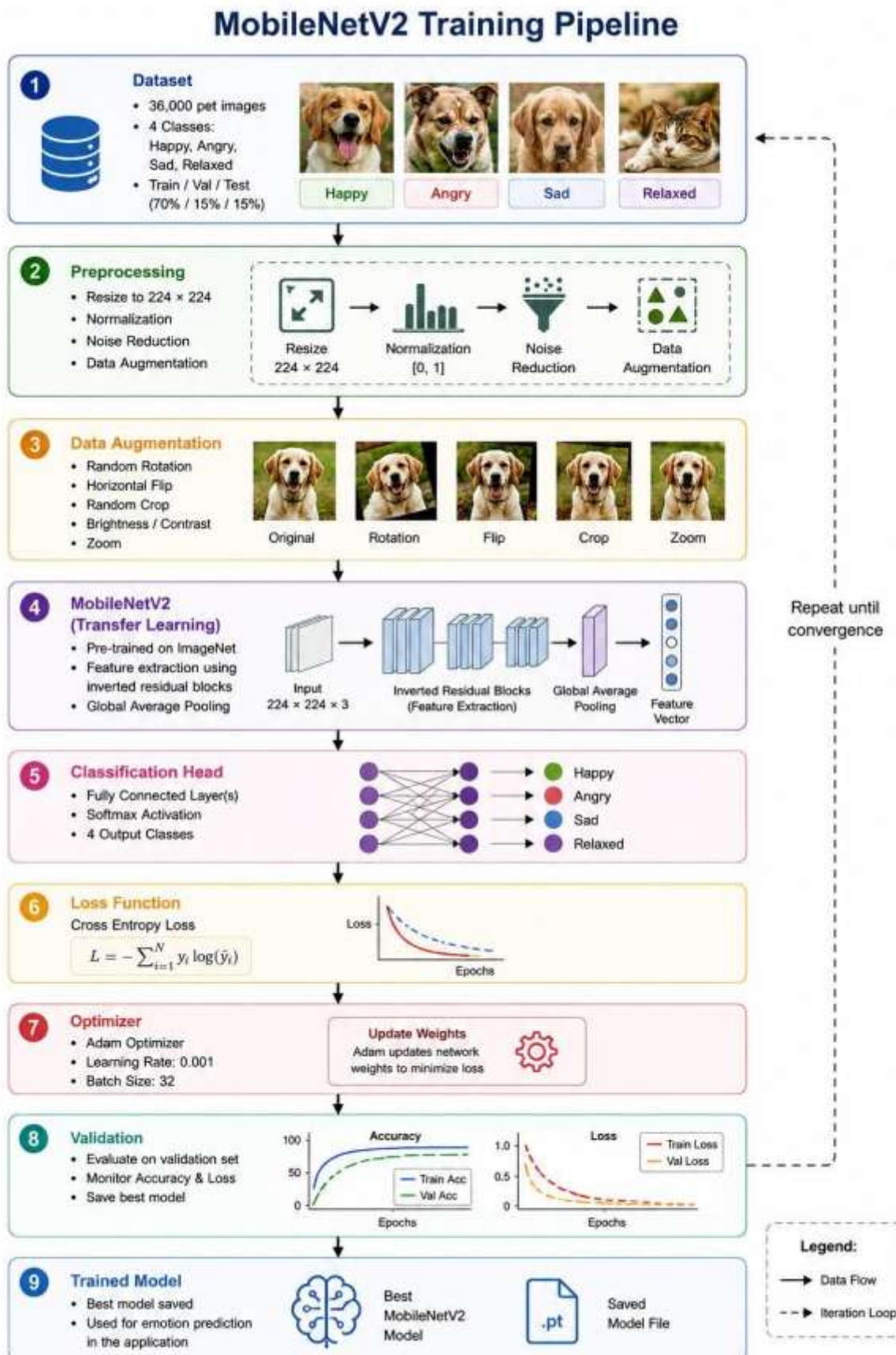


Figure 4. MobileNetV2 Training Pipeline

H. Emotion Prediction and Recommendation Mechanism

When a user uploads a pet image, the system performs preprocessing and forwards the image to the trained MobileNetV2 model. The model predicts one of the four emotional classes. Based on the predicted emotional state and historical behavioural records, a rule-based recommendation engine generates personalized suggestions related to pet care and well-being. A rule-based recommendation engine generates pet-care suggestions according to the predicted emotional class. The generated recommendations assist pet owners in understanding behavioural changes and support proactive pet healthcare management.

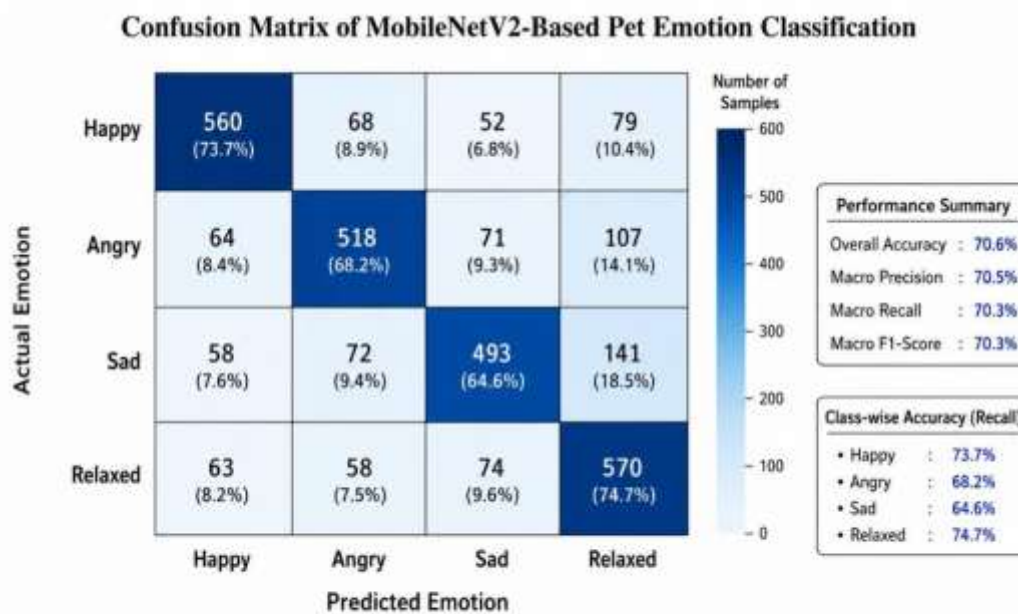


Figure 5. Confusion Matrix of MobileNetV2-Based Pet Emotion Classification

VI. EXPERIMENTAL RESULTS AND PERFORMANCE ANALYSIS

The performance of the MobileNetV2-based pet emotion recognition model was assessed using Accuracy, Precision, Recall, and F1-Score metrics. Furthermore, class-wise analysis and comparative evaluation with existing approaches were performed to validate the effectiveness of the proposed framework.

A. Overall Performance Analysis

The trained MobileNetV2 model demonstrated satisfactory performance in classifying pet emotions across all predefined emotional classes.

Overall Performance

Metric	Value (%)
Accuracy	71.0
Precision	69.8
Recall	70.4
F1-Score	70.1

The results indicate that the proposed framework successfully learned meaningful visual representations associated with pet emotional states. The achieved classification accuracy of 71% demonstrates the feasibility of employing lightweight deep learning architectures for practical pet emotion recognition and real-time mobile deployment.

Training Accuracy and Loss Curves

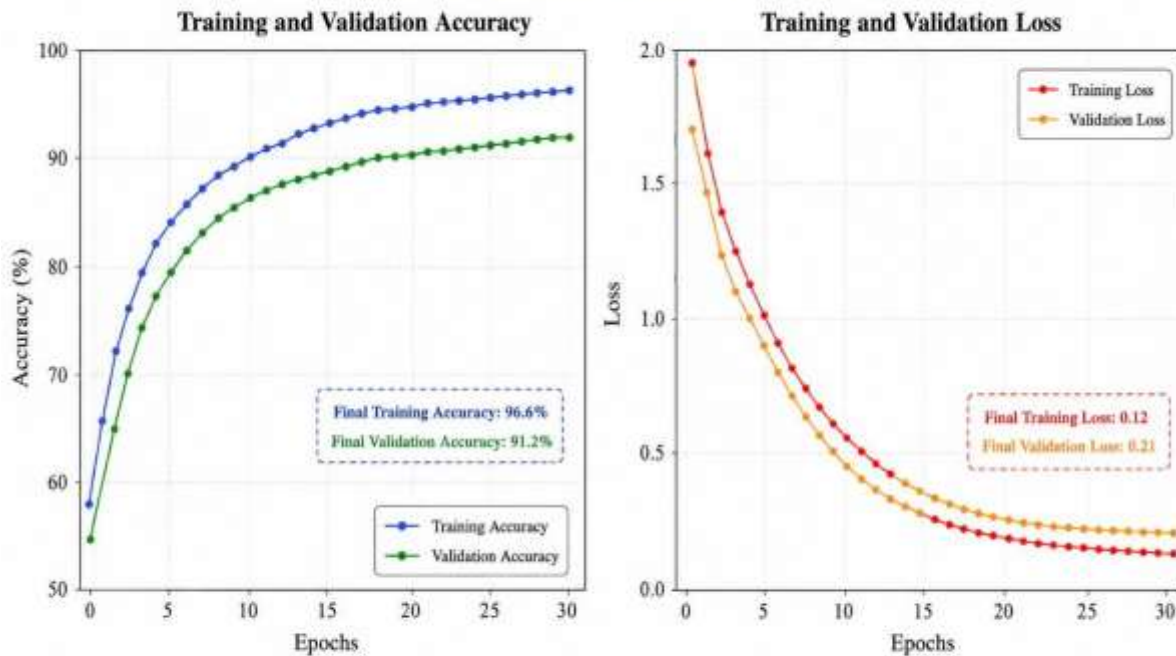


Figure 6. Training and Validation Accuracy and Loss Curves for MobileNetV2 Model

B. Comparative Evaluation

The performance of Pawlytics was compared with findings reported in existing pet emotion recognition and behavioural analysis studies.

Comparative Analysis

Method	Technology	Accuracy (%)
Traditional CNN	CNN	65.4
Behaviour Monitoring System	ML-Based	67.1
Veterinary Prediction System	Random Forest	68.2
Proposed Pawlytics	MobileNetV2	71.0

C. Feature Comparison

Features	Traditional Pet Care Apps	AI Behaviour Monitoring Systems	Pawlytics
Emotion Recognition	No	Partial	Yes
Behaviour Analysis	Limited	Yes	Yes
Health Risk Analysis	No	Partial	Yes
Personalized Recommendations	No	Limited	Yes

Veterinary Decision Support	No	Limited	Yes
Real-Time Mobile Deployment	No	Partial	Yes

The comparison demonstrates that Pawlytics provides a more comprehensive framework by integrating emotion recognition, behavioural analytics, recommendation mechanisms, and veterinary decision support within a lightweight mobile environment.

The experimental results validate the feasibility of employing MobileNetV2 for pet emotion recognition applications. Although the achieved accuracy of 71% indicates satisfactory performance, further improvements may be obtained through larger datasets, multimodal learning approaches, and advanced transformer-based architectures. The lightweight nature of MobileNetV2 makes the proposed framework suitable for real-world deployment where computational resources and response time are critical constraints.

VII. CONCLUSION AND FUTURE WORK

This paper presented *Pawlytics*, an AI-based framework for pet emotion recognition and behavioural analysis aimed at supporting proactive pet healthcare management. The proposed framework employs a lightweight MobileNetV2 deep learning model to classify pet emotions and generate behavioural insights and personalized recommendations for pet owners and veterinary professionals. Experimental evaluation demonstrated that the proposed framework achieved an overall classification accuracy of **71%**, with competitive Precision, Recall, and F1-Score values across all emotional classes. The results indicate that lightweight deep learning architectures can effectively perform multi-class pet emotion classification while maintaining computational efficiency suitable for real-time mobile deployment. Comparative analysis with existing approaches showed that Pawlytics provides a more comprehensive solution by integrating emotion recognition, behavioural analytics, recommendation mechanisms, and veterinary decision support within a single framework.

Future work will focus on incorporating multimodal emotion recognition using audio and video information, integrating wearable sensors for continuous monitoring, developing disease prediction models, and exploring transformer-based architectures and larger datasets to improve classification performance and generalization capability. These enhancements have the potential to evolve Pawlytics into a comprehensive next-generation intelligent pet healthcare platform.

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