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Cat Body Language Recognition Using Computer Vision in an Android Application

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ABSTRACT

Understanding cat behaviour is essential for fostering healthy human-cat relationships, but its inherent complexity frequently leads to misunderstandings. This study introduces Emeowtions, an innovative Android application employing artificial intelligence (AI) to decipher cat emotions and body language in real-time. Addressing market gaps for comprehensive tools, Emeowtions integrates the YOLOv8n object detection model with a custom-trained multi-label classification model for cat emotion and body language analysis. The custom model was developed based on the CRoss Industry Standard for Data Mining (CRISP-DM) framework and trained using transfer learning with MobileNetV3 on a custom curated dataset of annotated cat images. Built using the Waterfall methodology, the application allows users to obtain real-time, AI-driven insights via their smartphone camera. Beyond that, it provides a hybrid recommendation system suggesting tailored behaviour suggestions, a user feedback loop for model refinement, and a direct chat interface for veterinary consultations. Technical evaluation showed the AI model achieved a recall of 0.742. Overall, Emeowtions offers a valuable, practical tool that demonstrates AI's capability to reduce misinterpretations of cat behaviour, ultimately fostering healthier human-animal relationships and contributing to improved cat welfare.

Keywords: Cat Body Language Recognition, Cat Emotion Recognition, Computer Vision, Mobile Application, Multi-label Classification, Object Detection, Recommendation System

INTRODUCTION

Achieving harmonious human-cat interactions requires comprehensive understanding of cat behavior. However, this is a complicated task due to the subtlety of cat communication (Santovito et al., 2022; Xu, 2024). Cats utilize a wide array of vocalizations, facial expressions, and body language to convey distinct emotional states or intentions. Unlike more overtly expressive animals like dogs, feline body language is nuanced, often leading to misinterpretation (Xu, 2024). Furthermore, cats may mask stress or discomfort with stoic behaviour, attempting to resolve issues independently (Santovito et al., 2022; Xu, 2024). These challenges contribute to significant global issues, including cat abandonment, health degradation, and human injuries.

Misconceptions or insufficient understanding of cat behaviour among cat owners greatly contributes to the relinquishment or abandonment of cats. A study by (Powell et al., 2023) found that animal shelters in the United States (US) received about 3 million cats in 2019, and 17.67% of them were euthanized, which accounted for approximately 58% of all shelter euthanasia. (Powell et al., 2023) also found that at least 25% of those cats were relinquished personally by their owners due to behavioural issues such as aggression. According to another research by (Zhao, 2020), a study conducted at an animal shelter in England found that 38% of cats were returned after adoption citing behavioural issues. These concerning statistics show that a significant number of humans relinquish or abandon their cats due to inadequate understanding of cat behaviour.

Animal shelters are stressful environments for animals due to unusual stimuli, inadequate social interaction, limited freedom, and various factor. A study by (Santovito et al., 2022) found that shelter environments can induce stress, fearful, or aggressive behaviours in animals that otherwise behaved normally prior to entering shelters. In Sweden, an estimated 80% of shelters were found to have experienced abnormal behaviours in shelter cats such as fearfulness and aggression, most likely a result of poor welfare. The stressful state of shelter cats could lead to weakened immune system and increase chances of illnesses. Furthermore, behavioural signs which exhibit stress or discomfort often go unnoticed due to shelter overcrowding and the inherent subtlety of cats' body language. There is ongoing research regarding methods of monitoring shelter animals but are mostly ineffective as they involve time-intensive and laborious manual work (Eagan et al., 2022).

Misinterpretation or ignorance of cat body language signs that exhibit aggression often leads to human injuries. According to the (World Health Organization, 2024), cat bites make up 2% to 50% of injuries caused by animal bites. In the US, approximately 66,000 people end up in emergency rooms as a result of cat bites every year. Although rarely fatal, these hospitalizations are generally a result of infection such as cat scratch disease (CSD) due to cat scratches or bites. Thus, it is imperative to ensure that cat owners better understand cat body language so that they can pick up signs of aggression before aggressive reactions occur.

To this end, this study details the creation of an integrated solution involving an AI model for cat emotion and body language recognition, embedded within an Android application offering behavioural insights, recommendations, user feedback channels, and access to veterinary advice. Such an integrated approach has proven effective in delivering tailored insights and personalized recommendations across various domains such as food delivery services, enhancing user understanding and decision-making (Liem et al., 2023).

LITERATURE REVIEW

Cat Communication and Body Language

Cats employ a complex array of communication methods, including vocal, visual, olfactory, and tactile signals, to convey their emotional states and intentions (InternationalCatCare, 2018; Tavernier et al., 2020; Xu, 2024). Among these, visual communication or body language is particularly rich and nuanced, offering significant insights if correctly interpreted. Key indicators of a cat's emotion are expressed through various body language types, such as overall posture, facial expressions, visual cues from other body parts like the tail, and specific movements like kneading or slow blinking (Gerken, 2023; Sharma, 2024). The subtlety of these signals often leads to misinterpretation by humans, highlighting the need for tools that can aid in accurately decoding cat behaviour.

Evolution of Ethology and Technological Aids

Ethology, the scientific study of animal behaviour, has progressively incorporated technological advancements to enhance research capabilities. Initial methodologies heavily relied on direct behavioural observation and the meticulous construction of ethograms, which are detailed catalogues of species-specific behaviours (Egerton, 2016; Stanton et al., 2015). The field later saw the integration of veterinary behavioural medicine, applying clinical approaches to address animal behaviour problems (Horwitz & Houpt, 2020). More recently, the advent of wearable devices such as trackers or biologgers as well as Internet of Things (IoT) systems enable remote, continuous data collection on animal activity and physiology, but this may pose limitations regarding intrusiveness, connectivity, and accuracy (Holton et al., 2021; Ullmann et al., 2023). Presently, computer vision technology offers non-invasive methods for analysing animal behaviour from visual data (Fernandes et al., 2020).

Computer Vision Techniques

Computer vision, a subfield of AI, equips systems with the ability to interpret and understand visual information from the world, often leveraging Convolutional Neural Networks (CNNs), a type of machine learning (ML) model architecture. Several computer vision tasks are particularly relevant for animal behaviour analysis. Image classification is fundamental, assigning a label such as a specific animal species or behaviour to an entire image (Jajodia & Garg, 2019). Object detection and object tracking go further by locating and following specific instances of animals in an image or video sequence (Chen et al., 2023). Image segmentation provides pixel-level classification, allowing for precise highlighting of an animal's body outline (Dai et al., 2021). Pose estimation identifies the spatial configuration of an animal's body parts by locating keypoints such as joints, offering detailed insights into posture and movement (Ferres et al., 2022).

Recommendation Systems

Recommendation systems are designed to filter information and provide users with personalized suggestions. Generally, these systems fall into categories such as content-based filtering, collaborative filtering, and hybrid recommendation systems. Content-based filtering systems recommend items similar to those a user previously liked based on item attributes. Collaborative filtering systems suggest items based on the preferences of similar users. Hybrid recommendation systems combine multiple approaches to leverage their respective strengths and mitigate weaknesses (Ko et al., 2022). Although widely used in e-commerce and media, the application of sophisticated hybrid recommendation systems remains a largely unexplored area to provide tailored advice for animal behaviour management, presenting an opportunity for innovation (Ko et al., 2022; Ritika, 2024). For such systems to be effective when implemented in mobile

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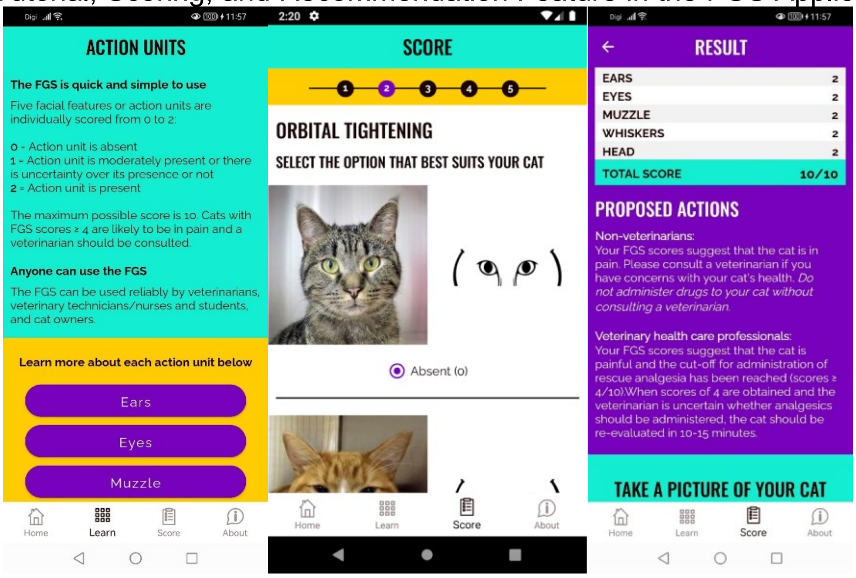
applications, critical factors such as performance expectations and user habits must be considered (Alamanda et al., 2021).

Similar Applications

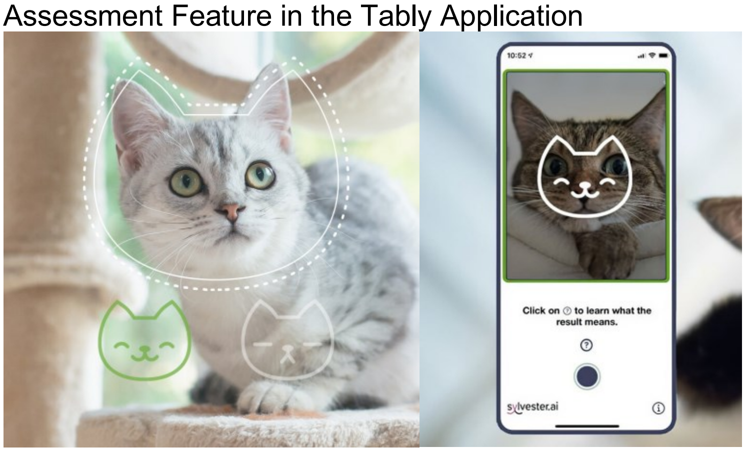
The Feline Grimace Scale (FGS) application provides a structured, clinically validated framework for assessing acute pain in cats based on facial expressions (Monteiro et al., 2023; Steagall Laboratory, 2025). Its strengths lie in its established methodology and usability for learning and manually scoring pain. However, its reliance on manual user input for scoring makes it prone to human error, especially for users unfamiliar with subtle cat facial cues. Moreover, its functionality is limited to a rule-based pain assessment without broader emotion or behaviour analysis.

Figure 1. Tutorial, Scoring, and Recommendation Feature in the FGS Application



Tably advances on the FGS concept by employing a CNN to automatically analyse a cat's facial expressions for pain assessment (Sylvester, 2022). This addresses the manual input limitations of the FGS app and can aid in early detection of health issues. However, Tably's analytical capabilities are currently limited to pain detection, not encompassing a wider spectrum of emotions or behaviours.

Figure 2. Pain Assessment Feature in the Tably Application

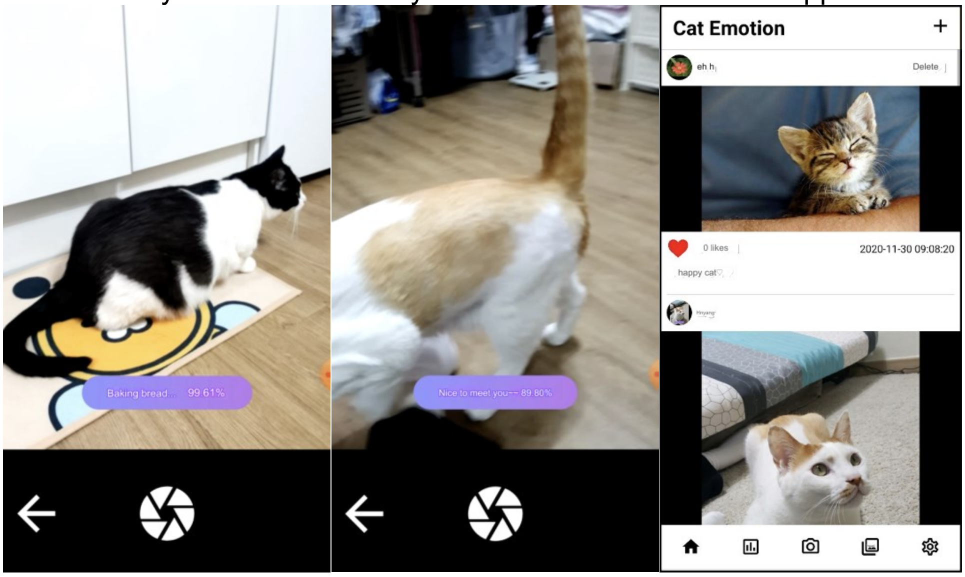


Source: Sylvester (2022)

CatEmotion utilizes a CNN to predict a cat's emotion by autonomously analysing its tail (Jang et al., 2021). This allows users to gain insights without direct, manual observation.

The primary drawback is its limited range of predictable emotions and singular focus on the tail, potentially missing body language cues expressed through other body parts.

Figure 3. Tail Analysis and Community Feature in the CatEmotion Application



Although these existing applications offer valuable contributions to specific aspects of cat welfare or behaviour assessment, they collectively reveal a significant gap in the market for a more comprehensive, integrated solution. Common limitations include a narrow focus on singular body language types (e.g., only facial expressions for pain, or only tail positions for basic emotions), a restricted range of detectable emotions, and a lack of sophisticated recommendation systems to guide users on appropriate actions or behavioural improvements. To address these shortcomings, this project developed Emeowtions, an AI-powered Android application designed to offer a more holistic approach to understanding cat behaviour. Table 1 provides a detailed feature comparison between Emeowtions and the aforementioned similar applications, highlighting Emeowtions' broader capabilities. Notably, Emeowtions aims to recognize a wider array of emotions by analysing multiple body language types. It uniquely incorporates a hybrid recommendation system, cat profiles for personalized insights, a user rating system for model feedback, and integration with veterinary clinics for consultation purposes.

Table 1. Feature Comparison Between Emeowtions and Similar Applications

Feature	FGS	Tably	CatEmotion	Emeowtions
Cat emotion and body language recognition technique	Rule-based	CNN	CNN	CNN
Recommendation system	Rule-based	N/A	N/A	Hybrid
Body language types recognized	Facial expressions	Facial expressions	Tail	Facial expressions, posture, and key body parts
Emotions recognized	Pain or no pain	Pain or no pain	Neutral, curious, happy	Neutral, happy, scared, angry
Body language tutorial	Available	N/A	N/A	Available

Cat profile	N/A	N/A	N/A	Available
Rating system	N/A	N/A	N/A	Available
Integration with veterinary clinics	N/A	N/A	N/A	Available
Community	N/A	N/A	Available	N/A
Dashboard	N/A	N/A	N/A	Available

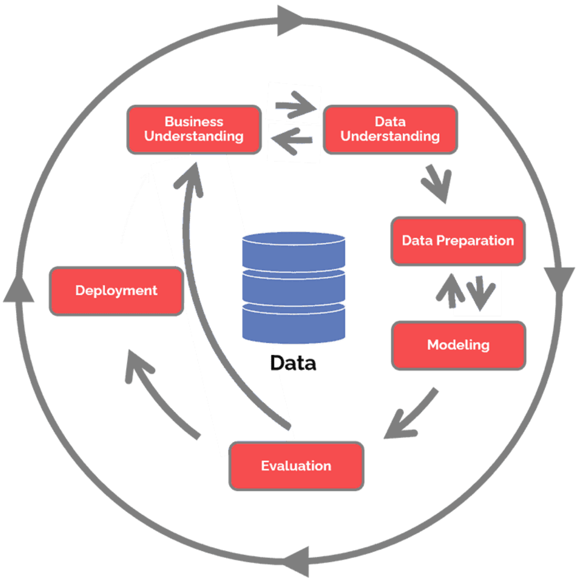
RESEARCH METHOD

The project adheres to the CRISP-DM framework for implementation of the AI models and the Waterfall methodology for the Android application. CRISP-DM was selected for its comprehensive approach to ML projects and iterative flexibility (Hotz, 2024), while Waterfall provided a structured sequence suitable for the application's well-defined requirements (Atlassian, 2025).

AI Model Development

The AI component comprising an object detector for cat detection and a multi-label classifier for emotion and body language analysis follows relevant phases of the CRISP-DM framework. The foundational Business Understanding phase established the project's objectives to address issues in cat behaviour interpretation and was completed in the early stages alongside the Android application's requirements gathering.

Figure 4. CRISP-DM Framework



Source: Hotz (2024)

Cat Detector

The implementation of the cat detector begins with the Data Understanding phase. Given the availability of robust state-of-the-art (SOTA) object detection models pre-trained on large-scale datasets like Common Objects in Context (COCO) which includes a "cat" class (Lin et al., 2015), this phase validated the suitability of these pre-trained models, eliminating the need for the Data Preparation phase. The Modelling phase involved a comparative review of SOTA models (e.g., SSD MobileNet, Faster R-CNN, YOLO) based on performance metrics such as mean average precision (mAP) and inference speed. mAP is a comprehensive metric that evaluates object detection accuracy by summarizing precision and recall across all classes. YOLOv8n was selected as the most suitable model due to its ideal balance between performance and computational efficiency. Next, Evaluation involved assessing the model's cat detection capability on a curated set of diverse cat images. Finally, the Deployment phase involved converting the selected model to the TensorFlow Lite (TFLite) format for optimization and integration into the Android application.

Cat Emotion and Body Language Classifier

Data Understanding

This phase established the dataset requirements of specific cat emotions (e.g., angry, happy, neutral, scared) and defined body language cues for training the classifier. Initial dataset reviews highlighted the need for custom data collection. Consequently, web scraping using Selenium on Google Images followed by manual filtering yielded a raw dataset of 1,232 images. This dataset was managed in Roboflow for subsequent processing.

Data Preparation

This phase involved manual multi-label annotation of the 1,232 images in Roboflow, assigning one emotion and relevant body language labels per image. Data was cleaned by removing images with obstructed or irrelevant content. Roboflow was utilized for final preprocessing, including auto-orienting images to prevent misinterpretation of cues, resizing all images to a consistent 224x224 pixels for model input, and automatically splitting the dataset into 80% training, 10% validation, and 10% testing sets. To further enhance dataset diversity and size particularly for minority classes, data augmentation techniques such as rotation, width shifts, height shifts, horizontal flips, and adjustments to brightness, contrast, and saturation were subsequently performed using PyTorch.

Modelling

This phase focused on developing the Emeowtions classifier. MobileNetV3Small was selected as the base architecture due to its efficiency and proven performance on mobile CPUs, crucial for Android deployment (Howard et al., 2019). Transfer learning was employed, loading pre-trained ImageNet weights into MobileNetV3Small with its top layers excluded to allow for custom classification heads. Initially, the base model layers were frozen. The custom head included a GlobalAveragePooling2D layer, followed by Dense layers with Rectified Linear Unit (ReLU) activation, and a final Dense output layer with sigmoid activation, appropriate for multi-label classification. The model was compiled in Keras using the Adam optimizer and BinaryCrossentropy loss function. To optimize performance and mitigate model overfitting, an iterative finetuning approach was applied to tune hyperparameters including learning rate, epochs, and batch size. Architectural enhancements were made by unfreezing top layers of the base model, adding L2 regularization, BatchNormalization, and Dropout layers. EarlyStopping and ReduceLROnPlateau callbacks were used to cease training when performance plateaued and dynamically adjust learning rate to reduce risks of overfitting.

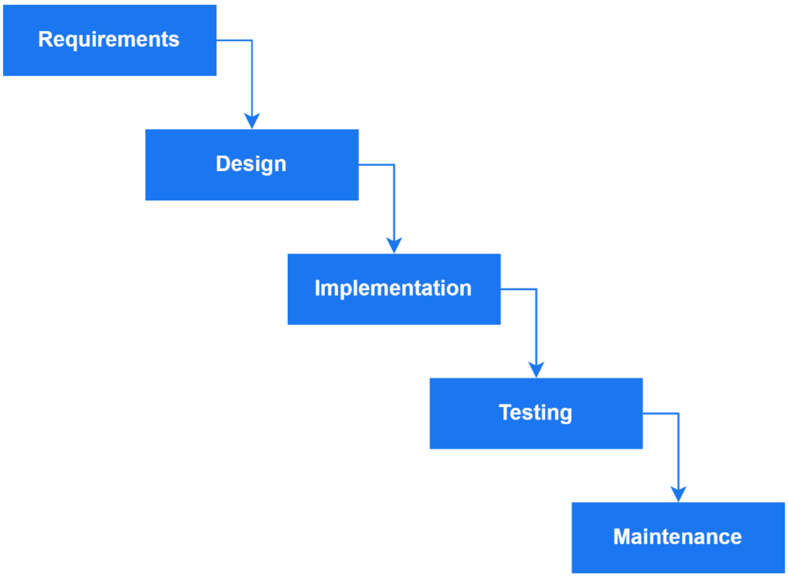
Evaluation

The evaluation strategy for the Emeowtions classifier, established prior to training, centered on assessing its technical performance and alignment with project objectives. The primary evaluation metrics chosen were recall and loss. Recall indicates the model's ability to correctly identify all actual instances of a specific emotion or body language present in an image. Loss quantifies the disparity between predictions and actual labels. These metrics were supported by secondary metrics including precision, Area Under the Precision-Recall curve (AUC-PR), binary accuracy, subset accuracy. Performance was systematically tracked on the training, validation, and held-out test sets across hyperparameter tuning iterations and architectural changes. Visualizations such as learning curves, confusion matrices per class, and AUC-PR curves were plotted to provide deeper insights into model behavior and identify areas of overfitting or underfitting. The overall aim was to verify the model's capability to classify cat emotions and body language in diverse, real-world scenarios effectively enough for practical deployment.

Deployment
Finally, deployment involved preparing the model for integration into the Android application. This consisted of converting the trained Keras model into the TFLite format. This conversion optimizes the model for on-device inference, reducing its size and improving computational efficiency on mobile devices, which is a critical requirement for real-time analysis within the application.

Android Application Development
The development of the Emeowtions Android application followed the Waterfall methodology. This sequential software development lifecycle model ensured a structured progression through distinct development stages.

Figure 5. Waterfall Methodology



Requirements
This initial phase was conducted concurrently with the AI models' Business Understanding phase, involving the identification of real-world problems related to cat behaviour misinterpretation and definition of core system requirements for Emeowtions. This included an extensive study of existing technologies such as computer vision and recommendation systems, followed by review of similar applications like FGS, Tably, and FGS to identify functional needs and potential gaps that could be addressed by Emeowtions, forming a checklist for subsequent development.

Design
This phase focused on creating a comprehensive blueprint for the Emeowtions application. This involved developing various design elements to visualize system architecture, features, and user workflows. Key outputs included flowcharts for major processes like cat body language analysis and recommendations, Unified Modeling Language (UML) diagrams to detail system structure and interactions, database designs for the Firestore NoSQL database, and wireframes for the user interface (UI) using Figma.

Implementation

During implementation, the actual development of the Emeowtions Android application was performed in Android Studio. This included building the user interface, integrating the trained TFLite AI models, and developing all planned system features such as the cat body language analysis module, the hybrid recommendation system, cat profile management, veterinary clinic integration, and administrative modules. Data preprocessing and model training activities were conducted on Visual Studio Code and Google Colab, respectively, with Git and GitHub used for version control.

Testing

This phase involved comprehensive quality assurance testing. Functional testing, including unit and integration tests, was conducted to verify that the application fulfilled all specified requirements, ensuring all individual modules and combined system components operated correctly. Non-functional testing assessed aspects such as the AI model's inference speed on mobile devices as well as application security to ensure user data protection and system reliability.

Maintenance

This is a post-deployment phase that involves ongoing monitoring of the Emeowtions application for user feedback, potential bugs, and performance issues. This phase ensures continued system stability, good user experience, and allows for the development and release of fixes or updates as needed.

RESULTS

Cat Detector Performance

To select an efficient cat detector suitable for mobile deployment, several SOTA models pre-trained on the COCO dataset were compared based on their mAP and inference speed. As shown in Table 2, YOLOv8n demonstrated a strong balance between mAP and speed. Specifically, YOLOv8n achieved a mAP of 37.3 and an inference speed of 80.4 ms on a 640x640 pixel input, establishing it as the best choice for cat detection within the Emeowtions application.

Table 2. Performance Comparison of SOTA Object Detection Models

Model	mAP	Speed (ms)
SSD MobileNet V1 FPN	29.1	48
SSD MobileNet V2 FPNLite	28.2	39
Faster R-CNN ResNet50 V1	29.3	53
Faster R-CNN ResNet101 V1	31.8	55
Faster R-CNN ResNet152 V1	32.4	64
Faster R-CNN Inception ResNet V2	37.7	206
YOLOv8n	37.3	80.4

Cat Emotion and Body Language Classifier Performance

The Emeowtions model for cat emotion and body language classification was evaluated on a test set. As recorded in Table 3, the model achieved an overall recall of 0.742 and a loss of 0.349. This recall value indicates that the model successfully identified approximately 74% of true emotion and body language cues across all tested images.

Table 3. Performance of Cat Emotion and Body Language Classifier

Metric	Value
Precision	0.823
Recall	0.742
Loss	0.349

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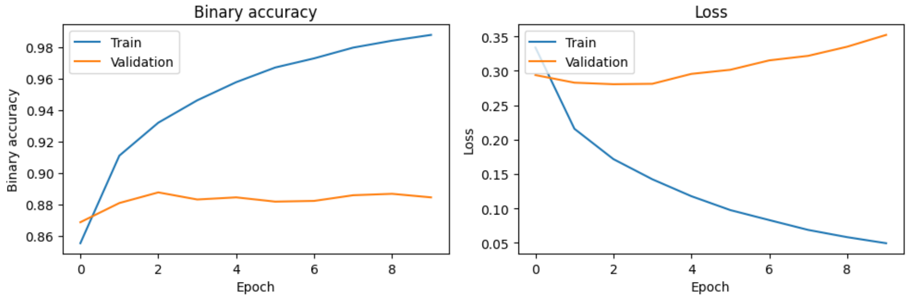
AUC-PR	0.949
Binary Accuracy	0.918
Subset Accuracy	0.268

The performance graphs in Figure 6 depict training and validation performance over epochs, illustrating the model's convergence and final relationship between training and validation metrics. The discrepancy between the training and validation metrics shows signs of overfitting, indicating that the model may be performing well on the training data but struggling to generalize to unseen data.

Figure 6. Recall and Loss Graphs of the Emeowtions Model



Based on results in Table 4 and Table 5, per-class analysis on the test set revealed varying performance across the 18 target classes. For instance, among emotion categories, the "angry" class achieved the highest recall of 0.941, while the "scared" class had the lowest recall of 0.560. In terms of specific body language cues, the model demonstrated high recall for visually distinct features such as "tail_up" (0.947 recall) and "posture_arched_back " (1.000 recall). Conversely, recall was comparatively lower for classes like "ears_flat", "posture_small," "tail_neutral," and "tail_tucked," suggesting greater difficulty in distinguishing these more subtle or ambiguous features. Despite these variations, the overall recall achieved on the test set confirmed the model's capability to fulfill the primary requirement of classifying diverse cat emotion and body language cues from images in practical scenarios.

Table 4. Performance Metrics of Emotion Classes

Class	Recall
angry	0.941
happy	0.896
neutral	0.697
scared	0.560

Table 5. Performance Metrics of Body Language Classes

Class	Recall
ears_flat	0.500
ears_up	0.833
eyes_large_pupils	0.645
eyes_narrowed	0.621
eyes_small_pupils	0.548
mouth_fangs	0.882
posture_arched_back	1.000
posture_exposed_belly	0.750
posture_neutral	0.684
posture_small	0.222

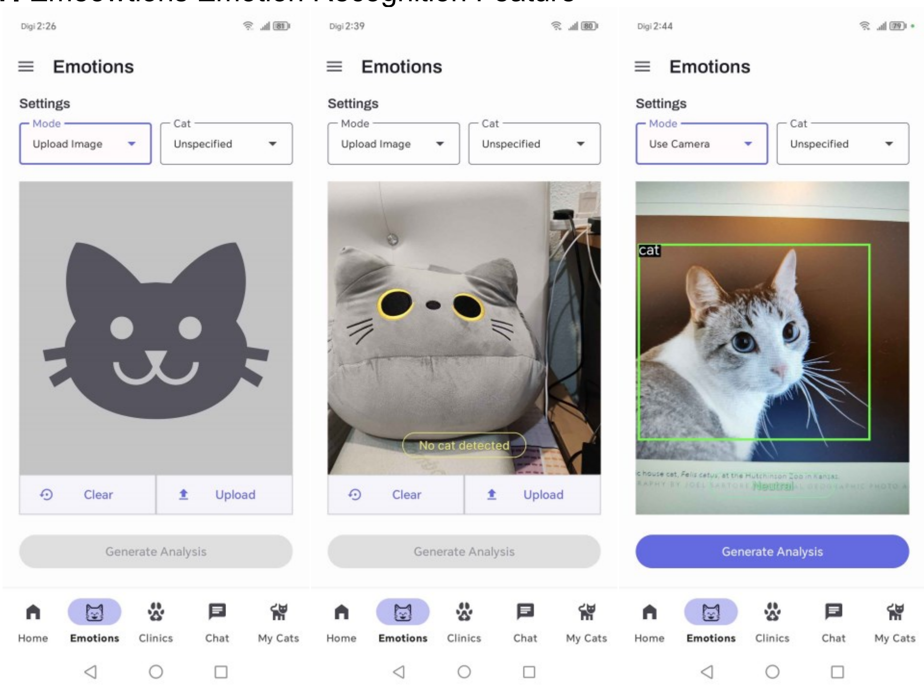
posture_stretch	0.800
tail_neutral	0.625
tail_tucked	0.538
tail_up	0.947

Emeowtions Android Application

Emotion Recognition

The core Emotion Recognition feature enables AI-driven analysis of a cat's emotion and body language. Users can initiate analysis via image upload or the smartphone camera. The system can also link the analysis to a saved cat profile for personalized recommendations. Upon successful cat detection by the cat detector, the Emeowtions classifier predicts the emotion and identifies body language cues, making the detailed analysis report accessible.

Figure 7. Emeowtions Emotion Recognition Feature



Body Language Analysis and Behavioural Recommendations

The application generates a detailed analysis report sectioned into a summary, body language details, and recommendations. The summary presents the predicted emotion, cat name, and analysed image. The body language section lists cues classified by the Emeowtions model with descriptions and confidence values. The recommendations section offers behaviour preservation or improvement strategies tailored to the detected emotion and cat characteristics, with each strategy showing a user-based helpfulness rating, reflecting a hybrid recommendation approach.

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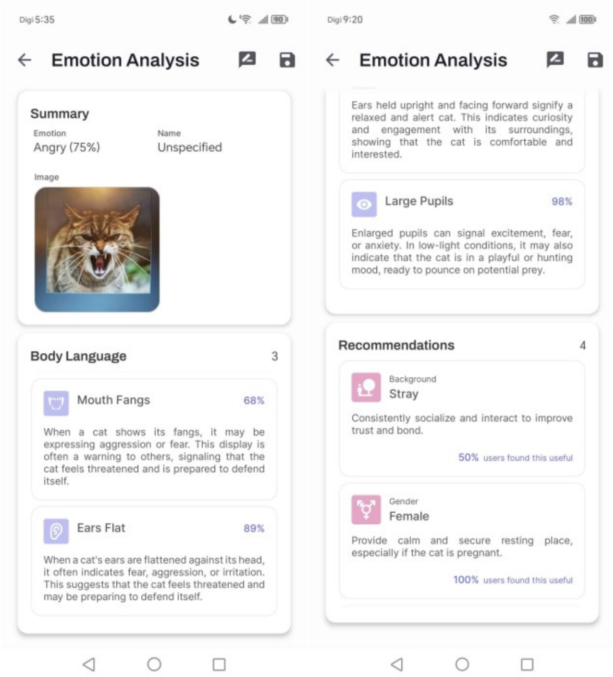
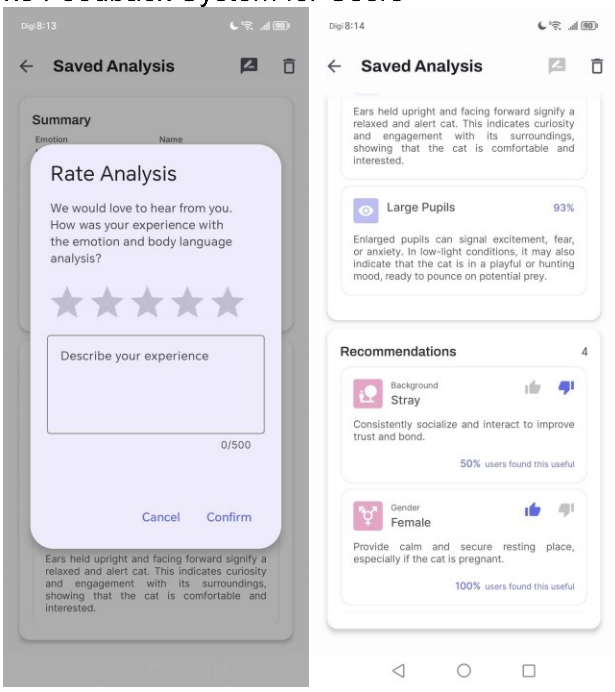
Figure 8. Emeowtions Body Language Analysis and Behavioural Recommendations Feature



Feedback System

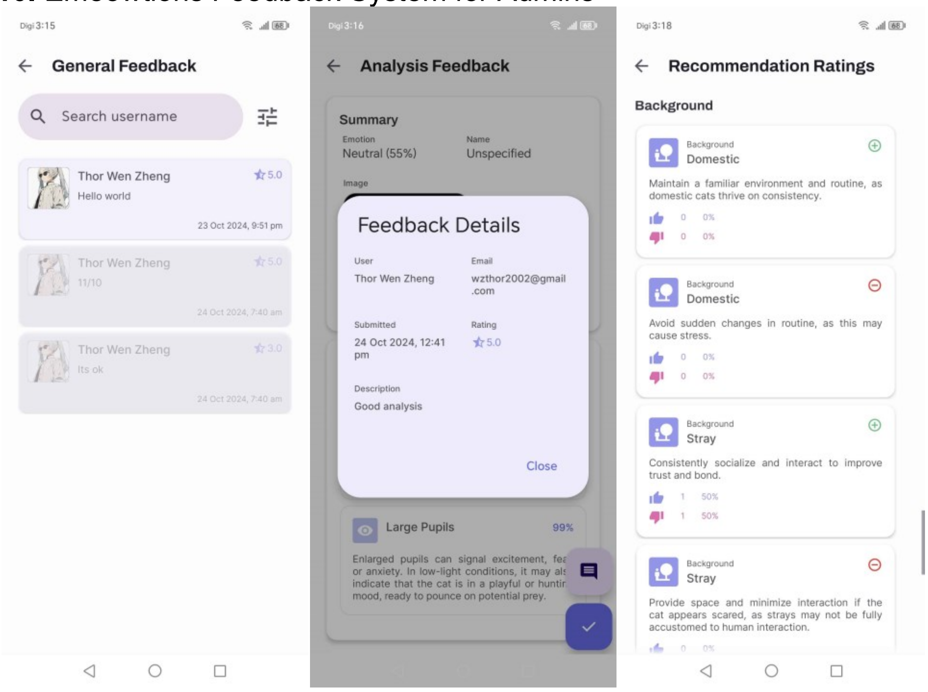
The feedback system facilitates user input and administrative review. Users can rate and provide textual feedback on the model’s analysis via a dialog within the analysis report. Users can also rate the helpfulness of recommendations via a like or dislike. This user-submitted feedback which includes ratings and descriptions is stored in the Firestore database.

Figure 9. Emeowtions Feedback System for Users



System admins can then access an "Analysis Feedback" page listing all submitted feedback. Admins can review the user's comments in the context of the original analysis report. The overall ratings of all behavioural recommendations can also be viewed in the “Recommendation Ratings” page. This enables a feedback loop for potential model refinement, issue tracking, and future enhancements of the recommendation system.

Figure 10. Emeowtions Feedback System for Admins



Veterinary Clinics

Emeowtions facilitates user access to veterinary services through a dedicated "Clinics" feature. Users can browse a directory of all registered and approved veterinary clinics, with options to search by clinic name. Each clinic listing displays essential information such as its logo, name, user rating, and address. Selecting a clinic provides access to a detailed profile page, which offers more comprehensive information about the clinic, lists its available veterinarians, and displays aggregated user reviews.

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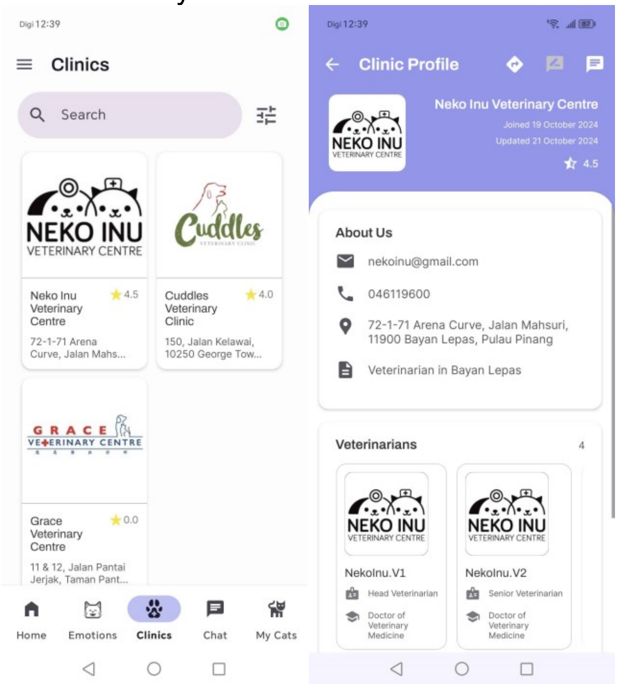
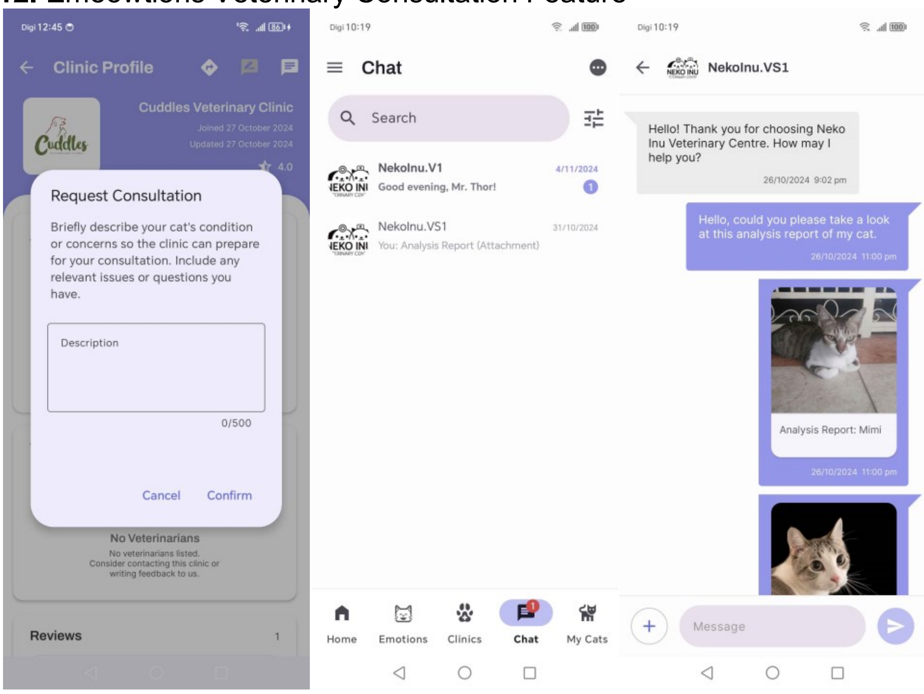
Figure 11. Emeowtions Veterinary Clinics Feature



Veterinary Consultation

From a clinic's profile, users request consultation by submitting a description of their cat's issue. Once this request is accepted by veterinary personnel, a private and secure chat session is established. Users can manage and access their ongoing consultations via a central "Chat" page, which displays all active conversations. The chat interface allows for real-time text-based communication with veterinary professionals and enables users to attach previously saved Emeowtions analysis reports, providing valuable context for the consultation.

Figure 12. Emeowtions Veterinary Consultation Feature



DISCUSSION

This study addressed challenges in cat communication by developing Emeowtions, an AI-driven Android application for recognizing cat emotions and body language and providing behavioural guidance. The project's significance lies in its integrated approach, combining a multi-label AI model with a user-friendly mobile platform featuring personalized recommendations and veterinary access, addressing a notable gap in current technological aids for cat owners.

The Emeowtions system successfully met its primary objectives. A functional AI model, achieving an overall test set recall of 0.742, was developed for identifying key emotions and various body language cues from images using transfer learning with MobileNetV3Small and iterative refinement. This model was integrated into the Emeowtions Android application via TFLite, powering the "Emotion Analysis" feature. A rule-based, hybrid personalized recommendation system was also implemented, offering practical guidance based on the AI's output and user-provided cat characteristics. Furthermore, a user feedback mechanism for AI predictions and a veterinary chat consultation system were successfully incorporated, enhancing the application's utility and support capabilities.

Compared to existing applications, Emeowtions offers a broader analytical scope. While applications like Tably focus on facial pain assessment and CatEmotion analyses tail movements for limited emotions, Emeowtions processes multiple visual cues for a wider array of emotions and specific body language signals. Unlike FGS application's manual input and basic suggestions, Emeowtions automates analysis and provides more context-aware hybrid recommendations. This comprehensive approach that incorporates a personalized recommendation system and veterinary consultation services clearly distinguishes Emeowtions from prior works.

CONCLUSION

This project successfully developed and demonstrated Emeowtions, an AI-powered Android application capable of recognizing cat emotions and body language from images, providing users with actionable behavioural insights. The system integrates an object detection model with a multi-label classification model into a cat detection and emotion prediction pipeline. Key features include AI-driven emotion and body language analysis, a tailored recommendation system, user feedback mechanisms, and veterinary consultation capabilities, which were implemented to address the project objectives. The Emeowtions application represents an advancement in applying AI to enhance human understanding of cat behaviour. By providing an accessible tool for deciphering subtle behavioural cues, this work contributes to fostering healthier human-cat relationships and empowering owners to make more informed decisions regarding their pets' welfare. The findings suggest that such integrated AI systems have considerable potential as practical aids in daily pet care. Furthermore, this project underscores the potential of deep learning for nuanced animal behaviour analysis and highlights opportunities for further refinement in model accuracy and the development of more sophisticated recommendation algorithms. For general readers and cat enthusiasts, Emeowtions offers a significant step towards decoding cat behaviour, encouraging more empathetic and informed interactions. Ultimately, this project sets the stage for future innovations where AI-driven insights are seamlessly integrated into animal behaviour monitoring and welfare.

LIMITATION

Although the achieved model accuracy fulfils practical requirements, the Emeowtions model did not reach SOTA performance levels, with recall values varying considerably across different behavioural labels. Notably, certain subtle body language cues like "posture_small" proved challenging for the model. The potential misclassification of critical negative emotions like “angry”, presents a safety consideration if users misinterpret these as positive emotions, highlighting a need for continued accuracy improvements. Practical constraints of the application include its reliance on internet connectivity for features like cat profiles and the recommendation system. Moreover, the application only has Android compatibility and excludes support for Apple iPhone users who represent a significant market segment of approximately 28.58% (Backlinko, 2024).

Future work should prioritize refining the Emeowtions model's performance. This can be pursued by expanding the training dataset with more diverse samples for underrepresented body language types, potentially improving recall consistency across all labels. Multi-task learning may also address dimensionality issues by using separate model heads to predict different behavioural aspects from a shared model backbone. Performance optimization techniques such as post-training quantization or quantization-aware training could enhance model speed and efficiency for on-device deployment with minimal accuracy trade-offs. To address application limitations, future enhancements could incorporate offline capability by caching commonly viewed cat profiles and behavioural recommendations locally, thereby improving accessibility. Furthermore, developing a cross-platform version using frameworks like Flutter or React Native would significantly broaden the user base, making Emeowtions accessible to both Android and iPhone users as well as extending its potential impact in promoting better human-cat relationship globally. Additionally, future development must prioritize ethical considerations like data privacy, AI transparency, and user trust, particularly as AI applications grow increasingly personalized (Shouran & Ali, 2024).

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DECLARATION OF CONFLICTING INTERESTS

The authors declare no conflict of interest.

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