RESEARCH-ARTICLE

Intelligent Systems for Comprehensive Dog Management

MENUSHA E. KATIPEARACHCHI, Sri Lanka Institute of Information Technology, Colombo, Sri Lanka

OMESH SACHETHANA, Sri Lanka Institute of Information Technology, Colombo, Sri Lanka

GANGULI N. A. GUNAWARDENA, Sri Lanka Institute of Information Technology, Colombo, Sri Lanka

DUVINDU C. RUWANARA, Sri Lanka Institute of Information Technology, Colombo, Sri Lanka

JENNY KRISHARA, Sri Lanka Institute of Information Technology, Colombo, Sri Lanka

DHARSHANA KASTHURIRATHNA, Sri Lanka Institute of Information Technology, Colombo, Sri Lanka

Open Access Support provided by:

Sri Lanka Institute of Information Technology

Published: 28 June 2025

ICIT 2024: 2024 the 12th International Conference on Information Technology (ICIT)
December 13 - 15, 2024
Kuala Lumpur, Malaysia

ICIT '24: Proceedings of the 2024 the 12th International Conference on Information Technology (ICIT) (December 2024)
https://doi.org/10.1145/3718391.3727886
ISBN: 9798400717376

Intelligent Systems for Comprehensive Dog Management

Menusha E. Katipearachchi
Sri Lanka Institute of Information Technology
dept. of Computer Science and Software Engineering
Malabe, Western Province, Sri Lanka
it2111377@my.sliit.lk

Omesh Sachethana
Sri Lanka Institute of Information Technology
dept. of Computer Science and Software Engineering
Malabe, Western Province, Sri Lanka
it21143236@my.sliit.lk

Ganguli N. A. Gunawardena
Sri Lanka Institute of Information Technology
dept. of Information Technology
Malabe, Western Province, Sri Lanka
it21150302@my.sliit.lk

Duvindu C. Ruwanara
Sri Lanka Institute of Information Technology
dept. of Computer Science and Software Engineering
Malabe, Western Province, Sri Lanka
it21005862@my.sliit.lk

Jenny Krishara
Sri Lanka Institute of Information Technology
dept. of Information Technology
Malabe, Western Province, Sri Lanka
jenny.k@sliit.lk

Dharshana Kasthurirathna
Sri Lanka Institute of Information Technology
dept. of Computer Science and Software Engineering
Malabe, Western Province, Sri Lanka
dharshana.k@sliit.lk

Abstract

In recent years, the integration of advanced technologies with canine welfare has gained significant attention, leading to the development of comprehensive platforms for dog management. The "Research Pooch-Paw" initiative addresses the multifaceted needs of dog owners and stray dog populations through an innovative platform that incorporates machine learning, wearable sensors, and real-time data processing. The platform facilitates early disease detection, behaviour analysis, and health monitoring using IoT-enabled devices, and provides personalized care guidance. Additionally, it includes features for stray dog identification and emergency response using deep learning algorithms and image processing techniques. The research underscores the potential of leveraging modern technology to enhance the quality of life for dogs and improve the effectiveness of canine welfare strategies.

CCS Concepts

• **Information systems** → Information systems applications; Mobile information processing systems; • **Computing methodologies** → Machine learning; Machine learning approaches; Neural networks; • **Applied computing** → Life and medical sciences; Health informatics.

Keywords

Machine learning, Internet of Things (IoT), health monitoring, Dog behaviour analysis, Stray dog management, Canine disease detection

ICIT 2024, Kuala Lumpur, Malaysia

ACM ISBN 979-8-4007-1737-6/2024/12
https://doi.org/10.1145/3718391.3727886

ACM Reference Format:
Menusha E. Katipearachchi, Omesh Sachethana, Ganguli N. A. Gunawardena, Duvindu C. Ruwanara, Jenny Krishara, and Dharshana Kasthurirathna. 2024. Intelligent Systems for Comprehensive Dog Management. In *2024 the 12th International Conference on Information Technology (ICIT) (ICIT 2024), December 13–15, 2024, Kuala Lumpur, Malaysia.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3718391.3727886

1 Introduction

In recent years, the intersection of technology and animal welfare has garnered increasing attention, particularly in the realm of canine care. As the bond between humans and dogs continues to deepen, there is a growing demand for comprehensive platforms that cater to the holistic well-being of these beloved companions. In response to this need, the "Research Pooch-Paw" initiative aims to develop an innovative canine welfare platform integrating advanced technologies and data-driven approaches to address various aspects of dog health, behaviour, care, and management.

Canine health is a multifaceted domain encompassing various aspects, including disease detection, behaviour analysis, and care guidance. Traditional methods of canine healthcare often rely on reactive approaches, where interventions occur after the onset of symptoms or issues. However, with the advent of cutting-edge technologies and data analytics, there exists a tremendous opportunity to revolutionize the way research approach canine welfare. By leveraging machine learning algorithms, wearable sensor technologies, and real-time data processing capabilities, it becomes feasible to proactively predict, monitor, and manage canine health conditions [1] [2].

Despite the growing awareness of canine welfare, several challenges persist in effectively addressing the diverse needs of dog owners and stray dog populations. These challenges include the timely identification of canine diseases, understanding and interpreting dog behaviour, providing accessible care guidance, and managing stray dog populations in urban environments. Existing solutions often lack integration, accessibility, and scalability, thereby hindering their widespread adoption and efficacy.

The primary objectives of "Research Pooch-Paw" are as follows. To identify canine skin-related diseases and other visual abnormalities using advanced image processing techniques and machine learning algorithms, thereby facilitating early prediction and recommending appropriate remedies [3]. This research develops an IoT-enabled dog belt with sensors to monitor heartbeat anomalies and activity levels. Building on studies that explore wearable sensors for dog behaviour analysis and heartbeat anomalies [1] [4], this research aims to improve canine health monitoring through advanced IoT technology.

To establish a comprehensive knowledge base for dog care, encompassing nutrition, grooming, exercise, and medical care, supplemented by a user-interactive chat system for personalized guidance and breed selection assistance [5]. To conduct a comprehensive census of stray dog populations utilizing deep learning algorithms and image processing techniques, coupled with an emergency reporting system to facilitate prompt intervention and management strategies. The primary users of the platform are dog owners seeking to enhance the health, well-being, and quality of life of their pets. The key deliverables include an Internet of Things (IoT) device equipped with sensors for data collection and a mobile application offering user-friendly interfaces for accessing various features and functionalities.

2 Literature Review

The application of machine learning in skin disease recognition has shown substantial improvements in diagnostic accuracy and efficiency. ML models, particularly convolutional neural networks (CNNs), have been greatly used to analyse and classify skin lesions based on images. These models can identify subtle patterns and features that might be overlooked by human eyes, thereby enhancing diagnostic precision. A systematic review by Zhang et al. highlights the effectiveness of ML methods in skin lesion research, observing their ability to handle large datasets and improve diagnostic outcomes through image segmentation and classification processes [3]. Additionally, a study by Rathnayaka et al. demonstrated the use of an intelligent system for detecting skin diseases in dogs, employing ontology-based clinical information extraction, utilized machine learning techniques to enhance the accuracy of diagnosis in veterinary applications, further showcasing the broad applicability of ML in the field of dermatology across different species [6].

Deep learning, a subset of ML, employs neural networks with multiple layers to model complex patterns in data. It has been particularly successful in image-based diagnostics. In a study by Leach et al., deep learning models demonstrated superior performance in identifying various skin conditions by learning from a vast number of labelled images. This was also seen from A. Iyer's study. The models were able to differentiate between diseases with similar visual characteristics, which is a common challenge in dermatology [7] [8].

The use of deep learning (DL) in veterinary medicine, particularly for diagnosing dog skin diseases, has been explored in several studies, highlighting its potential to alleviate the diagnostic burden on veterinarians by providing accurate, real-time assessments. For example, a study by Hwang et al. utilized a CNN to classify images of dog skin diseases into categories such as hypersensitivity allergic, bacterial dermatosis, and fungal infections, achieving high accuracy and reliability. Additionally, Srinivasu et al. demonstrated the effectiveness of combining MobileNet V2 with LSTM for skin disease classification, further validating the capability of DL models in this domain [9] [10].

The classification of canine behaviour using wearable sensors, particularly accelerometers, has been a focal area of research. Studies, by Eerdekens et al., demonstrate how accelerometer data can classify behaviours such as walking, sniffing, and playing, while also highlighting challenges in distinguishing similar activities [1]. Additionally, Sinitca et al., emphasize the importance of modular software design and integrating multiple sensors to enhance the accuracy and scalability of behaviour classification systems [11].

The accurate monitoring of heart rate in canines is critical for assessing their health, especially during physical activities. The studies conducted by Brugarolas et al. and M. Foster et al. investigates the design and performance of wearable heart rate sensors specifically designed for dogs. The paper discusses the challenges related to sensor placement, data accuracy, and the impact of various activities on heart rate measurements. This research provides valuable insights into the technical considerations for developing reliable heart rate monitoring systems [12] [13].

In addition to health monitoring, the integration of social media platforms with wearable devices for animals is emerging as a novel approach to enhancing pet care. The study by Rakshitha et al. explores how data collected from wearable devices can be shared on a social media platform to engage pet owners and veterinarians in discussions about pet health and behaviour. This integration can potentially lead to better-informed care decisions and foster a community of pet enthusiasts sharing valuable insights and experiences [14].

The development of exercise-based activity plans for dogs using machine learning recommendation systems has gained traction due to the need for personalized pet care. This research leverages breed, age, and weight goals to tailor exercise routines and integrates Large Language Model (LLM) APIs with a chat system for personalized interaction. Existing literature emphasizes the importance of data-driven approaches in dog care, influencing the design of the recommendation system [5].

Various studies have focused on improving the identification and monitoring of stray animals using modern machine learning and computer vision techniques. One such study investigated the use of Facenet and Dlib networks for dog identification, focusing on the accuracy of full body versus facial images of dogs. The results demonstrated that facial images provide more discriminative embedded vectors than full body images, with the average accuracy reaching 91.43% for facial images [15]. This insight is valuable for the image hashing technique in the research, as it suggests that focusing on facial features could enhance the accuracy of stray dog identification.

Another study explored the enhancement of the YOLOv5 algorithm for detecting stray cats and dogs in urban environments. By incorporating Soft-NMS and Merge-NMS algorithms, the researchers achieved a 2.2% improvement in detection accuracy compared to the standard YOLOv5 NMS algorithm [16]. This study highlights the potential for optimizing object detection algorithms, which could be applied to improve the performance of the image classification models used in the research.

Furthermore, research involving the integration of YOLOv5 with ML.Net for real-time dog detection in residential areas showcased the practical application of object detection models in a real-world setting. The system, which also sends SMS notifications when stray dogs are detected, demonstrated the effectiveness of combining detection and classification models with live video feeds [17]. This approach is like the real-time processing needs of research, particularly in verifying and classifying dog images captured by users.

Additionally, the "Lost and Found Dog" (LFD) mobile application focused on the development of a specialized database to assist in the rapid and effective search for lost dogs. The application's ability to maintain an up-to-date record of dogs provides a framework for the mobile application's database, which will store and manage the data of identified stray dogs [18]. The LFD application's emphasis on accessibility and efficiency can inform the user interface design of the mobile application, ensuring it meets the needs of users in a timely manner.

Recent research in image processing has advanced dog identification and care solutions. One study addresses the issue of lost dogs in Sri Lanka by utilizing a customized VGG16 model within a CNN framework, achieving over 90% accuracy in dog face recognition, thereby offering a practical solution for reuniting lost dogs with their owners [19]. Another study tackles the challenge of classifying a dog's age from a photograph, developing a novel architecture that combines CNN with Vision Transformer (ViT) models. This approach improves accuracy, particularly across different breeds, and highlights its potential in preventive veterinary medicine [20].

The study has identified several key requirements, including disease identification and recovery time prediction, behaviour analysis, heartbeat anomaly detection, stray dog management, dog exercise recommendation and personalised chatbot.

3 Methodology

The research project aims to develop an intelligent solution for identifying and managing stray dogs by integrating machine learning and image processing with health monitoring. It includes preprocessing images for optimal data, a recommendation engine for tailored exercise plans, and a system for detecting canine skin diseases using a specialized dataset. The project also explores canine behaviour analysis using deep learning and IoT technologies, promoting canine health and well-being while enhancing stray dog management.

According to Table 1, for the frontend, chose to implement a mobile application using Flutter, a UI toolkit for building natively compiled applications for mobile, web, and desktop from a single codebase. The application interfaces with a backend powered by Firebase, which serves as the database to store and retrieve the data, including images, model predictions, and dog patient records.

The disease detection system used a dataset of 9,450 images, with pre-processing ensuring consistency for the CNN model. Built in Python and optimized via Google Cloud AutoML, the CNN was integrated into a Flutter app for real-time dog skin disease diagnosis. Veterinarians can upload images, receive predictions, and provide feedback, which is stored in Firebase for ongoing model refinement, ensuring it adapts to new variations and improves over time.

Table 1: Overview of the Technology Stack

Component	Technology	Description
Model Development	Convolutional Neural Network (CNN), Feedforward Neural Networks (FNN) and K-Nearest Neighbours (KNN) in Python	Developed models
Model Optimization	Google Cloud AutoML	Used AutoML to improve the accuracy and performance of the CNN model
Frontend Development	Flutter	Implemented a mobile application for user interaction
Backend & Database	Firebase	Stored images, predictions, and user data
Machine Learning Framework	TensorFlow	Integrated TensorFlow model into the Flutter application for real-time prediction

Data collection for animal behaviour using Deep Learning involved an IoT-enabled dog belt to monitor canine movements. The dataset includes accelerometer and gyroscope readings from the dog's neck, capturing movement along the x, y, and z axes. The target variable is the specific behaviour exhibited, like "Walking." Before analysis, the data will be pre-processed with NumPy and scikit-learn for normalization and split into training and testing sets for model development and evaluation.

Chose an appropriate model for the classification task. Given that dealing with sensor data, a neural network model is suitable. Used TensorFlow to build the neural network architecture. Experimentation with different architectures, such as feedforward neural networks, allows us to find the best fit. Once the model is defined, train it using the training data. To assess the model's performance, employs various evaluation metrics, including accuracy, precision, recall, and F1-score. Cross-validation helps us understand how well the model generalizes to unseen data.

To monitor and classify heartbeat data as normal or anomalous, this model starts with data preprocessing by converting categorical variables like 'gender,' 'breed,' and 'state' into numerical values using label encoding. Standardization is applied to ensure features have zero mean and unit variance. The data is then split into training (70%) and testing (30%) sets, with one-hot encoding for binary classification. The FNN-based deep learning model, built with TensorFlow, includes multiple dense layers with ReLU activation and a dropout layer to prevent overfitting. Trained over 100 epochs, the model's accuracy is evaluated, and predictions are transformed back into class labels using np.argmax. This development draws on research addressing heart rate monitoring challenges in canines.

The personalized exercise-based activity plans given by machine learning recommendation system utilizes three algorithms: Support Vector Machine (SVM), K-Nearest Neighbours (KNN), and Naïve Bayes. Split the dataset, which includes information about the breed, age, and weight goals of the dogs, into training and testing sets. Then evaluated the accuracy of each algorithm using a confusion matrix. Based on this evaluation, the KNN algorithm was selected as the most suitable for this task due to its superior performance.

A comprehensive dog care knowledge base was developed using Pinecone, enabling a personalized chat system that covers diseases, treatments, and recommendations for dog owners. Implemented with Large Language Model APIs, the interactive system provides relevant, personalized information on various topics, including breed selection, by considering user preferences. Additionally, a daily report feature keeps users updated with the latest developments in dog care based on the knowledge base.

Stray dog identification and shelter location is conducted in several key stages, each utilizing specific machine learning and image processing techniques. This employs an image hashing technique to enable the identification of previously reported stray dogs. The image hashing algorithm generates unique hash values for each captured dog image, which are then compared against a database of previously reported stray dogs. If the hash value matches an existing entry, the system recognizes the dog as already reported; otherwise, it adds the new entry to the database. This method ensures efficient and accurate identification with minimal computational overhead.

To determine the age category of the dogs, a Convolutional Neural Network (CNN) is implemented. The CNN is trained using the dataset of 6000 labelled images, distinguishing between puppies and adult dogs. The network is designed with multiple convolutional and pooling layers to extract features that are relevant to age classification. The model is iteratively trained and validated to optimize its accuracy, with adjustments made to the architecture as necessary based on performance metrics.

An essential component of the system is the verification process that checks whether the user-submitted image depicts a dog. Before running the image hashing or CNN models, a deep learning algorithm is applied to ensure the correctness of the input. This model is trained using a diverse dataset of images, including various animals and objects, to accurately distinguish dogs from non-dog images. This step prevents erroneous data from entering the system, thereby improving overall reliability.

For the emergency posting feature, the application allows users to upload images and details about dogs in urgent situations without the need for complex processing. This feature is designed with a user-friendly interface, enabling quick and easy submission of posts. The posts include the dog's image, the nature of the emergency, and relevant details such as the location and time. The simplicity of this feature encourages user participation and ensures timely reporting of critical situations.

Finally, the entire application is rigorously tested in a real-world environment. Beta testing is conducted with a selected group of users who interact with the application under various conditions.

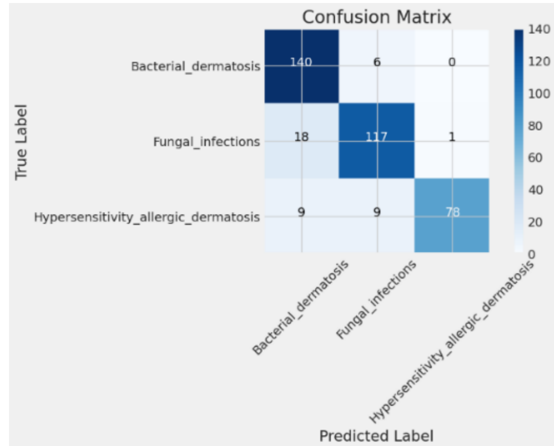

Figure 1: Confusion Matrix

Feedback is collected to identify any issues or areas for improvement. The application is then refined based on this feedback, ensuring that it meets the needs of its users and effectively contributes to the management of stray dogs in Sri Lanka.

4 Result and Discussions

4.1 Dog Skin Diseases Detection

The CNN model's performance was initially evaluated using precision, recall, and average precision, achieving an average precision of 0.867, with 87.7% precision and 80.1% recall. When using Google Cloud AutoML, the model's performance improved, with an average precision of 0.908 for fungal infections, 0.851 for hypersensitivity allergic reactions, and 0.867 for bacterial dermatosis, resulting in an overall average precision of 0.875. The confusion matrix in Figure 1 shows bacterial dermatosis with 140 true positives, 27 false positives, and 6 false negatives; fungal infections with 117 true positives, 15 false positives, and 19 false negatives; and hypersensitivity allergic dermatosis with 78 true positives, 1 false positive, and 18 false negatives.

The training and validation loss and accuracy were plotted over 25 epochs. The best epoch for validation accuracy was identified as epoch 17.

In Figure 2. The training loss remained low, while the validation loss showed an initial spike before stabilising. Training and Validation Accuracy: The training accuracy steadily improved, reaching close to 0.9, while the validation accuracy fluctuated, peaking at epoch 17

These results indicate that the model performs reasonably well, with some room for improvement in handling specific classes.

4.2 Dog Behaviour Analysis

The initial model achieved an accuracy of 43%, highlighting challenges in accurately classifying behaviours such as "Walking" and "Sniffing." To address this, a neural network with a feedforward architecture (FNN) was developed using features from the accelerometer and gyroscope. The improved model achieved a training accuracy of 81% and a testing accuracy of 75%. This improvement

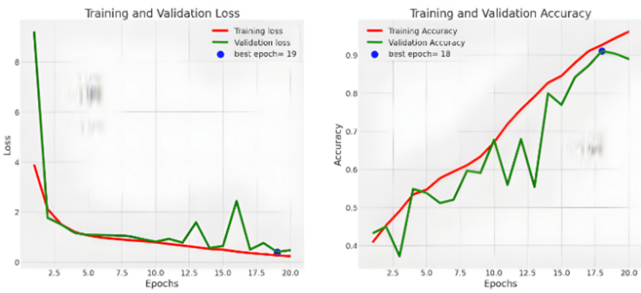

Figure 2: Training and Validation Accuracy and Loss

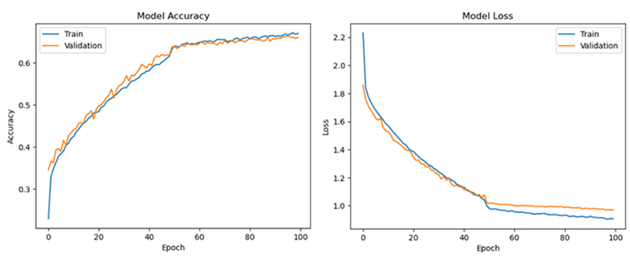

Figure 3: Training and Validation Accuracy and Loss

indicates better performance, though some overfitting is evident, suggesting the need for further optimization. These findings align with existing research that underscores the complexity of canine behaviour classification using sensor data [1] [2].

In Figure 3. the loss curves indicate effective learning with minimal overfitting, while accuracy curves show training accuracy at 81.95% and validation at 75.03%. The model performs well for dog behaviour analysis and heartbeat monitoring, though slight overfitting suggests room for further optimization.

4.3 Heartbeat Anomaly Detection

The heartbeat sensor model performed well, with a training accuracy of 90% after 100 epochs, effectively classifying heartbeat data into normal or anomalous categories. The model's architecture, which includes multiple dense layers and dropout, proved robust in handling physiological data. The preprocessing steps, including label encoding and standardization, were crucial for the model's success. These results are consistent with prior research on wearable heart rate sensors for canines, demonstrating the importance of rigorous preprocessing and a well-structured model [3] [4].

4.4 Exercise Recommendation

The models for Personalized Exercise Recommendation were trained using several architectures (Table 1), and according to Figure 4 and Figure 5 the best architecture was selected among them by considering the accuracy.

(1) was used to measure the accuracy as the number of samples correctly classified out of all the samples present in the test dataset.

$$Accuracy = \frac{TP + TN}{TP + \ FP + TN + FN} \tag{1}$$

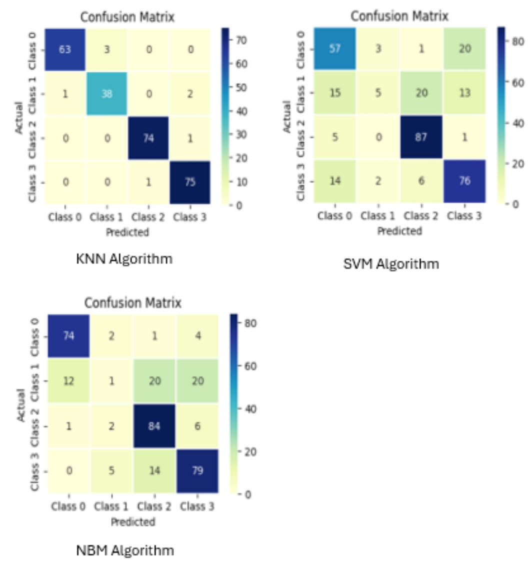

Figure 4: Comparison of confusion matrices

```
import pandas as pd
from sklearn.metrics import classification_report

# Assuming result DataFrame is already defined
result = result.T  # Transpose DataFrame to swap rows and columns

# Extract y_test and knn_predictions columns
y_test = result['y_test']
knn_predictions = result['knn_predictions']

# Generate classification report
report = classification_report(y_test, knn_predictions)

print(report)
              precision    recall  f1-score   support

           0       0.98      0.95      0.97        66
           1       0.93      0.88      0.90        43
           2       0.96      0.99      0.97        75
           3       0.96      0.99      0.97        76

    accuracy                           0.96       260
   macro avg       0.96      0.95      0.96       260
weighted avg       0.96      0.96      0.96       260
```

Figure 5: Classification Report

where,
TP = the number of true positive samples
FP = the number of false positive samples
TN = the number of true negative samples
FN = the number of false negative samples

(2) was used to measure the precision as the number of true predictions made by the model for a single class.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

where,
TP = the number of true positive samples
FP = the number of false positive samples

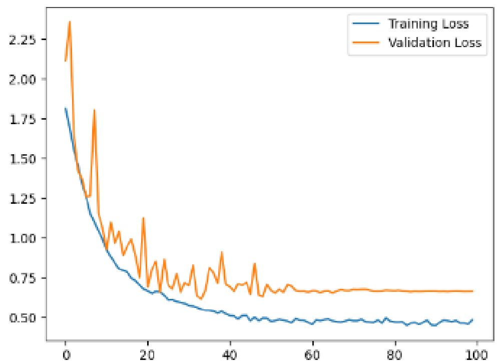

Figure 6: Training and Validation Loss

Figure 7: Dog Age Identification Model Accuracy

4.5 Stray Dog Census

The performance of the "Dog or Not" model, designed to verify whether the user-provided image depicts a dog, is illustrated in the graph shown in Figure 6. The model was trained over 10 epochs, demonstrating a steady increase in both training and validation accuracy. The training accuracy begins at approximately 0.70 and consistently improves, reaching above 0.90 by the 10th epoch. Similarly, the validation accuracy starts at around 0.75, experiencing fluctuations but ultimately showing an upward trend, peaking at approximately 0.87. This indicates that the model is effectively learning to distinguish between dog and non-dog images, though the gap between training and validation accuracy suggests potential overfitting. Further tuning of the model's parameters could be considered to ensure more generalized performance across diverse data.

The graph shown in Figure 7 depicts the training and validation accuracy of the "Dog Age Identification" model, which classifies images into puppy or adult categories. This model was trained over a more extended period of 100 epochs, during which the training accuracy consistently improves, eventually stabilizing above 0.85. In contrast, the validation accuracy shows significant volatility, particularly in the early epochs, fluctuating between 0.50 and 0.75 before stabilizing around 0.80. The instability in validation accuracy during the early stages indicates that the model may have encountered difficulty generalizing from the training data, potentially due to overfitting or data imbalance between puppy and adult dog images.

The difference in behaviour between the two models highlights the complexity of the tasks. While the "Dog or Not" model quickly converges and shows stable performance, the "Dog Age Identification" model requires more epochs to achieve similar stability, reflecting the greater challenge of classifying dog images by age. The results suggest that while both models are effective, the age classification task may benefit from additional data augmentation or regularization techniques to improve the robustness and generalization of the model. Future work could involve fine-tuning the hyperparameters or exploring alternative architectures to further enhance the performance of the age identification model.

5 Conclusion

"Research Pooch-Paw" is a quantum leap in the realm of canine science and welfare, as it integrates machine learning, the Internet of Things, and data-driven strategies. On top of that, developing a CNN-based model for skin disease detection and wearable sensors for behaviour monitoring shows completeness in the solution toward handling diverse challenges in the health management of dogs. In the same course, the victory of a mobile application for real-time disease detection and augmented accuracy metrics supported through Google Cloud AutoML are among the practices and potentials of more advanced technologies that add value to veterinary care.

But more than diagnostics, it extends the functionality of the platform to become a tool useful for both dog owners and vets with its personalized exercise recommendations and health monitoring features. All are meant to make "Research Pooch-Paw" answer to all changing needs in canine care through a never-ending system optimization process fed by continuous data collection and user feedback, thus enabling the bridging of technology with issues pertaining to the welfare of all pets. This development of advanced systems does not only contribute to the area of animal welfare technology but also sets a precedence for the use of intelligent systems in veterinary science.

Further development of "Research Pooch-Paw" is possible by creating an expanded database of skin conditions to enhance the accuracy of diagnosis, supplemented by additional sensors and AI analytics that provide further insight into canine behaviour. The platform's wider diffusion and constant refining are also made possible through collaboration with veterinary professionals and animal welfare organizations. These changes will enable the research to create new benchmarks in animal welfare technology and foster further innovation in pet care.

References

[1] A. Eerdekens, A. Callaert, M. Deruyck, L. Martens and W. Joseph, "Dog's Behaviour Classification Based on Wearable Sensor Accelerometer Data," *2022 5th Conference on Cloud and Internet of Things (CIoT)*, Marrakech, Morocco, 2022, pp. 226-231, doi: 10.1109/CIoT53061.2022.9766553.

[2] C. Kavitha and K. P. Kavitha, "A Chatbot System for Education NLP Using Deep Learning," *2023 Eighth International Conference on Science Technology Engineering*

and Mathematics (ICONSTEM), Chennai, India, 2023, pp. 1-7, doi: 10.1109/ICONSTEM56934.2023.10142830.
[3] Upadhyay, A., Singh, G., Mhatre, S., & Nadar, P. (2023). Dog Skin Diseases Detection and Identification Using Convolutional Neural Networks. SN Computer Science, 4(3). https://doi.org/10.1007/s42979-022-01645-5
[4] R. Brugarolas *et al.*, "Wearable Heart Rate Sensor Systems for Wireless Canine Health Monitoring," in *IEEE Sensors Journal*, vol. 16, no. 10, pp. 3454-3464, May15, 2016, doi: 10.1109/JSEN.2015.2485210.
[5] P. Chyan, "Decision Support System for Selection of Dog Breeds," 2018 International Seminar on Research of Information Technology and Intelligent Systems (ISRITI), Yogyakarta, Indonesia, 2018, pp. 343-346, doi: 10.1109/ISRITI.2018.8864327.
[6] R. M. N. A. Rathnayaka, K. G. S. N. Anuththara, R. J. P. Wickramasinghe, P. S. Gimhana, L. Weerasinghe and G. Wimalaratne, "Intelligent System for Skin Disease Detection of Dogs with Ontology Based Clinical Information Extraction," 2022 IEEE 13th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), New York, NY, NY, USA, 2022, pp. 0059-0066, doi: 10.1109/UEMCON54665.2022.9965696.
[7] Hwang, S., Shin, H. K., Park, J. M., Kwon, B., & Kang, M. (2022). Classification of dog skin diseases using deep learning with images captured from multispectral imaging device. Molecular & Cellular Toxicology, 18(3), 299–309. https://doi.org/10.1007/s13273-022-00249-7
[8] Iyer, A., Iyer, S., Hire, K. (2021). A Skin Disease Detection System Using CNN Deep Learning Algorithm. In: Reddy, V.S., Prasad, V.K., Wang, J., Reddy, K.T.V. (eds) Soft Computing and Signal Processing. Advances in Intelligent Systems and Computing, vol 1325. Springer, Singapore. https://doi.org/10.1007/978-981-33-6912-2_18.
[9] T. G. Debelee, "Skin Lesion Classification and Detection Using Machine Learning Techniques: A Systematic Review," Diagnostics (Basel, Switzerland), vol. 13, no. 19, p. 3147, Oct. 2023, doi: https://doi.org/10.3390/diagnostics13193147.
[10] P. N. Srinivasu, J. G. SivaSai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM," *Sensors*, vol. 21, no. 8, p. 2852, Apr. 2021, doi: https://doi.org/10.3390/s21082852.
[11] A. M. Sinitca, D. I. Kaplun, V. K. Kovrigin and A. Zamansky, "Software Architecture of the Automated Animal Behavior Analysis System," 2019 III International Conference on Control in Technical Systems (CTS), St. Petersburg, Russia, 2019, pp. 245-248, doi: 10.1109/CTS48763.2019.8973311.
[12] R. Brugarolas *et al.*, "Wearable Heart Rate Sensor Systems for Wireless Canine Health Monitoring," in IEEE Sensors Journal, vol. 16, no. 10, pp. 3454-3464, May15, 2016, doi: 10.1109/JSEN.2015.2485210.
[13] M. Foster, S. Mealin, M. Gruen, D. L. Roberts and A. Bozkurt, "Preliminary Evaluation of a Wearable Sensor System for Assessment of Heart Rate, Heart Rate Variability, and Activity Level in Working Dogs," 2019 IEEE SENSORS, Montreal, QC, Canada, 2019, pp. 1-4, doi: 10.1109/SENSORS43011.2019.8956771.
[14] R. Kasun, L. G. H. Mahesh, Y. A. D. I. Yapa, S. M. S. D. Suwendra, N. Kodagoda and K. Suriyawansa, "Zilla: An Animal Based Social Media Platform," 2019 International Conference on Advancements in Computing (ICAC), Malabe, Sri Lanka, 2019, pp. 267-272, doi: 10.1109/ICAC49085.2019.9103368.
[15] Zhang, Z., Li, S., Zhang, D., Chen, J., Chi, X., & Zhang, Z. (2023). Improvement of Soft-YOLOv5 Algorithm for Stray Cats and Dogs Detection. 2023 IEEE 6th International Conference on Pattern Recognition and Artificial Intelligence (PRAI), 35, 176–180. https://doi.org/10.1109/prai59366.2023.10332093.
[16] P. C. Galeno, D. P. Sale and E. M. B. Martin, "SMS-based Dog Detection in Residential Area using YOLOv5 and ML.Net," 2023 IEEE 11th Conference on Systems, Process & Control (ICSPC), Malacca, Malaysia, 2023, pp. 315-320, doi: 10.1109/ICSPC59664.2023.10420223.
[17] R. Promya, S. Thainimit, C. Charnsripinyo and Y. Koike, "Comparisons of Full Body and Facial Dog Identification," 2020 International Conference on Computational Science and Computational Intelligence (CSCI), Las Vegas, NV, USA, 2020, pp. 1641-1646, doi: 10.1109/CSCI51800.2020.00302.
[18] S. Chutichudet, T. Kanthathasiri, I. Ritsakunchai and D. Wongsawang, "LFD: Lost and found dog application on mobile," *2014* Third *ICT International Student Project Conference (ICT-ISPC)*, Nakhonpathom, Thailand, 2014, pp. 147-150, doi: 10.1109/ICT-ISPC.2014.69232
[19] S. Mazurek *et al.*, "Canine age classification using Deep Learning as a step toward preventive medicine in animals," 2022 17th Conference on Computer Science and Intelligence Systems (FedCSIS), Sofia, Bulgaria, 2022, pp. 169-172, doi: 10.15439/2022F226.
[20] S. Mazurek *et al.*, "Canine age classification using Deep Learning as a step toward preventive medicine in animals," 2022 17th Conference on Computer Science and Intelligence Systems (FedCSIS), Sofia, Bulgaria, 2022, pp. 169-172, doi: 10.15439/2022F226.