Deep-feed: An Internet of things-enabled smart feeding system for pets powered by deep learning

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ABSTRACT

Internet of things (IoT) encompasses a variety of connected devices and technologies designed to improve care, monitoring, and management of pets. IoT technology enables voice or app-driven control of these feeders, allowing pet guardians to remotely dispense food to their pets anytime. In this paper, a novel deep-feed network has been proposed that combines Image and sensor data classification. The inputs, such as camera (images) and sensor data, are sent to the preprocessing stages, where images are preprocessed using a Bilateral filter, and the data using preprocessing techniques such as tokenization, lemmatization, etc. The preprocessed images are sent to the neural network, like a convolutional neural network (CNN) for image classification and a bidirectional gated recurrent unit (BiGRU) to predict the dog's behavior. Next, these two networks are fused, and the fuzzy concept identifies whether the dogs are near the food or not in a cage. If the dog is near the food cage, the control unit will allocate the food and water through the water pump in the dog cage. Then the control unit gives the order to fill the food and water pumps and alerts the user to identify the food in a cage via the Blynk application. The accuracy of the suggested method can reach 99.95%, compared to 84.9%, 87.58%, and 93.91% for conventional models like the cat's monitoring and feeding systems via IoT (CMFSVI), petification, and global system for mobile communications/general packet radio service (GSM/GPRS). In comparison to the current approaches, the accuracy of the suggested methodology increased by 16.09%, 13.8%, and 3.75%, for existing models like CMFSVI, petification, and GSM/GPRS, respectively.

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1. INTRODUCTION

The Internet of things (IoT) has revolutionized various industries by connecting devices that share and gather data to enhance real-time monitoring, automation, and decision-making [1], [2]. Within this landscape, smart pet care systems have emerged as a promising application, providing pet owners with automated tools to ensure their pets are cared for even in their absence [3], [4]. Feeding pets a sufficient quantity of food at the suitable moment times is a crucial responsibility for owners, as poor nutrition can lead to various health issues in pets [5]. Traditional methods of feeding pets often lead to overfeeding or underfeeding, causing further health complications [6]. Automated pet feeders, controlled via apps or voice commands, offer a modern solution by allowing owners to dispense food remotely [7].

Pets require varying quantities of food and minerals based on their size [8]. As an alternative to conventional feeding techniques, automated pet feeders are growing in popularity among pet owners [9]. The device makes it convenient for pet guardians to ensure the feeding schedule and food amount [10]. The pet feeder with digital controls teaches the animal when and how to eat [11]. Owners may relax knowing their pets will have food and that they won't have to bother about feeding them by utilizing a pet feeder [12], [13].

Despite the advancements in automated pet feeders, many existing models lack the ability to accurately monitor pets' feeding habits or behaviors, which can lead to inefficiencies in ensuring the pet’s well-being [14]. Some systems fail to account for whether the pet is near the feeder or if the feeding schedules are being adhered to. This can cause delays or missed feeding times, directly affecting the pet’s health [15]. There is a need for more intelligent systems that can not only dispense food but also monitor and predict the pet's behavior to ensure timely feeding. To overcome these challenges, an innovative deep learning (DL) based pet feeding system (deep-feed) has been proposed for identifying the food in a cage. The major contribution of the work has been followed by:

- Initially, the data is collected from multiple sensors that monitor the pet’s environment. The sensor and image data are pre-processed using techniques such as bilateral filtering, tokenization, lemmatization, and stop word removal to filter and process text data for analysis.
- The preprocessed data is fed into a convolutional neural network (CNN) for image classification and a bidirectional gated recurrent unit (BiGRU) to predict the dog's behavior and verify if the pet is near the feeding zone.
- If the system predicts that the pet is near, it activates a control unit powered by an ESP8266, gives the order to fill the food and water pump, and the control unit alerts the user to identify the food in a cage via the Blynk application.
- The suggested Deep-Feed approach was evaluated based on a number of factors, including recall, accuracy, precision, and F1-score.
- The proposed work employs the combination of a deep learning method and multiple sensors, which provides automatic feeding of pets with a higher response time. The adoption of sensors and deep learning techniques in automatic feeding is a novelty that has not been employed in the existing techniques.

The following work is divided into three sections: Section 2 provides related works, and Section 3 provides one of the proposed deep-feed techniques. Section 4 contains the findings and a discussion. Section 5 presents a conclusion and future work.

2. LITERATURE REVIEW

In 2018, Chen *et al.* [16] presented a remote-control system with an IP camera and microcomputer. It is mobile and interactive in comparison to other smart pet feeders, which might improve the interaction between the owner and the animal. In 2020, Wang [17] presented a link contribution value model based on the communication network service. The experimental result illustrates that the suggested calculation model can provide focused advice for network risk mitigation.

In 2021, Razali and Lazam [18] suggested a big data processing smart pet feeder to help pet guardians ensure their pets are taken care of during their absence and in anticipating pet food shortages. The pet food level data can also be gathered by the system and utilized for time-series forecasting. In 2021, Shiddieqy *et al.* [19] suggested that an automatic pet feeding system be constructed utilizing a 3D printer and an open-source control. If the guardian has access to the Blynk application on their phone, and this machine can operate constantly and independently.

In 2021, Quiñonez *et al.* [20] developed two frameworks that utilize global system for mobile communications/general packet radio service (GSM/GPRS) communication networks and the Twitter social network to remotely control electrical equipment and a mobile application. This aims to ensure that dogs are fed appropriately and healthily by offering a food ration. In 2021, Rasyidi and Zin [21] introduced a cat's monitoring and feeding systems via IoT (CMFSVI) process for user observations, including design, material selection, and testing from a variety of angles. The purpose of this research is achieved by the CMFSVI, which measures the amount of kibble and water.

In 2021, Koley *et al.* [22] introduced an auto pet feeder prototype that would provide food and water for a variety of pets when their owners are absent from home. An ATMEGA32 microcontroller is utilized to operate the suggested framework. In 2022, Kim *et al.* [23] offered Petification, an IoT network built on the open-source Node-RED project and the message queue telemetry transport (MQTT) messaging protocol. We also looked at the automatic feeding amount accuracy of the meal and found that it was, on average, 88.38% correct.

In 2022, Kim and Moon [24] suggested integrating data from wearables and cameras to build a multimodal data-based method for identifying dog behavior. The video data depicts the dogs' movement area for dog recognition. In 2022, Kasnesis *et al.* [25] developed DL models that were installed on the wearable device, and this system was examined during two different search and rescue missions. In all situations, the rescue squad was alerted immediately. In 2024, studies [26], [27] built a DL model with UNet to identify the diseases on leaf. UNet is used to segment the portion where diseases are affected.

2.1. Research gap

A thorough review of the literature revealed the following research gaps in the proposed research challenge:

a. Although there have been a number of advances made in pet feeding system for identifying the food in a cage, a variety of obstacles persist concerning efficient pet feeding system in the cloud. Studies remain underway to formulate the innovative deep learning-based pet feeding (Deep-Feed) system for identifying the food in a cage.
b. The existing pet feeding techniques depend on several machine characteristics. Most of the techniques uses deep learning techniques for pet feeding. However, the literature review reveals that DL-based pet feeding can considerably improve dog behavior recognition accuracy.

The proposed Deep-Feed methodology overrides such drawbacks by improving scalability, low feeding accuracy, and manual structure dependency. The proposed Deep-Feed framework is provided in the upcoming section.

3. PROPOSED SYSTEM

In this work, an innovative DL based pet feeding system has been proposed (Deep-Feed) for identifying the food in a cage. The camera inputs (images) are sent to the preprocessing a bilateral filter is applied to sensor data to remove noise while preserving edges. For text Includes lowering casing, tokenization, lemmatization, and stop word removal to prepare text data for analysis. preprocessed images are sent to the neural network, like CNN for image classification and BiGRU to predict the dog's behavior. Next, these two networks are fused, and the fuzzy concept identifies whether the dogs are near the food or not in a cage. If the dog is near the food cage, the control unit will allocate the food and water pump in the dog cage. Then the control unit gives the order to fill the food and water pump and the control unit alerts the user to identify the food in a cage via the Blynk application. Figure 1 illustrates the overall conceptual diagram of the proposed Deep-Feed methodology.

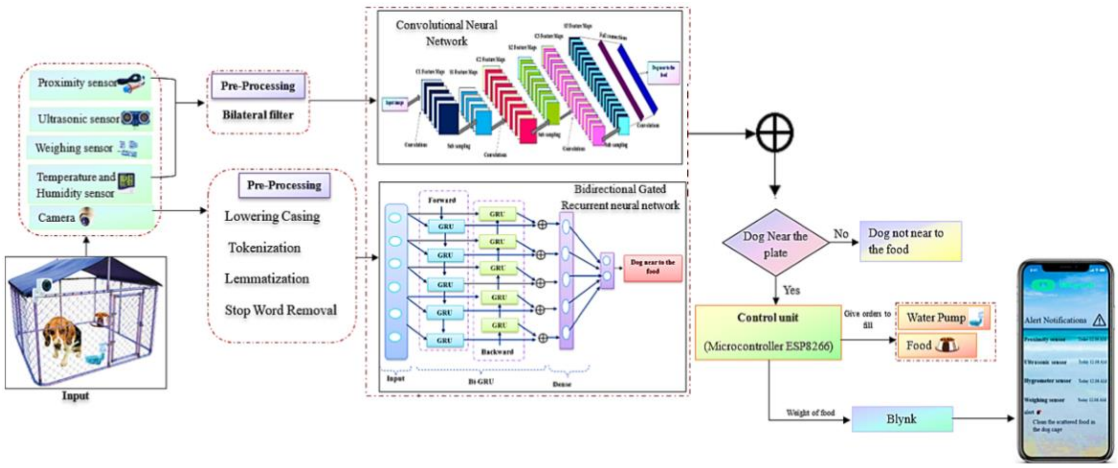


Figure 1. Proposed methodology

3.1. Sensors

In this research, we employed four types of sensors: proximity, ultrasonic, hygrometer, and weighing sensors. A proximity sensor uses electromagnetic waves, ultrasonic, infrared, or capacitive technologies to determine the distance between the sensor and the item. Ultrasonic sensor can detect objects in their environment and are useful for collision avoidance and obstacle detection. A weighing sensor used in various industries such as agriculture, manufacturing, and healthcare, for tasks like tracking inventory, and monitoring the progress of patients on weight loss plans. Humidity and temperature sensors are utilized to track and report the surrounding environmental conditions, particularly temperature and moisture levels.

3.2. Bilateral filter via preprocessing

The Bilateral filter plays an important role in boosting the small changes in the input images and lowering the noise. In comparison to a comparable Gaussian filter, a bilateral filter has the advantage of maintaining the edges across intensity variations. This algorithm calculates a local neighborhood's weighted sum of pixels. The output of a bilateral filter for an arbitrary pixel y can be formulated using (1) as,

$$I_y(y = m) = \frac{1}{Z_m} \sum_{n \in T} f_t\left(\left||m - n|\right|\right) e_s(I_m - I_n) I_n \quad (1)$$

where m and n are the coordinates for each pixel, T signifies the spatial area of $I_y(y)$. The combination of these parameters allows the bilateral filter to smooth the image while preserving important edge details, ensuring that regions with similar intensity values are blurred while distinct edges remain sharp.

3.3. Pre-processing digital input

Pre-processing in this study is classified into four categories: stop word removal, lemmatization, tokenization, and casing reduction. Lowercase word conversion (from NLP to nlp). Tokenization is the process of separating input data into distinct words. Lemmatization is a superior alternative to stemming since it considers word morphology. Stop words (a, an, the, etc.) are often used in writing.

3.4. Prediction via CNN and Bi-GRU

Prediction using CNNs and Bi-GRUs offers a robust framework for handling complex tasks such as time series forecasting, sequence classification, and natural language processing. In our suggested CNN model reduces the spatial dimensions of the feature map, helping to minimize overfitting and computational complexity. The fact that time series prediction problems include short-term health monitoring suggests that Bi-GRU can be used in this context. The input data of a health report represented as y_t. $t = (1, 2, \ldots, n)$. The outcomes of computing two GRU, equations 2 and 3, may be used to express the Bi-GRU.

$$\vec{h}_t = GRU_f\ (y_t, \vec{h}_{t-1}) \quad (2)$$

$$\overleftarrow{h}_t = GRU_b\ (y_t, \overleftarrow{h}_{t-1}) \quad (3)$$

In this equation, $\vec{h}_t$ and $\overleftarrow{h}_t$ represent the forward and backward GRU's respective states. Finally, it can classify whether the report is normal or abnormal. The following stages summarize Algorithm 1.

Algorithm 1. Deep feed
Step 1: Start
Step 1: Initialize sensors (proximity, ultrasonic, hygrometer, weighing)
Step 2: Initialize camera
Step 3: Connect to Blynk application
Step 4: Load CNN and Bi-GRU models
Main Loop:
Step 5: While (system is active):
Step 6: Capture image and read sensor data
Step 7: Apply bilateral filter to image
Step 8: Preprocess sensor data
Step 9: Extract CNN features from image
Step 10: Extract Bi-GRU features from sensor data
Step 11: Fuse CNN and Bi-GRU features
Step 12: Apply fuzzy logic to determine pet proximity
Step 13: If pet is near feeder:
Step 14: Check food and water levels
Step 15: If levels are low, notify user via Blynk
Step 16: Sleep for predefined interval
Step 17: Stop

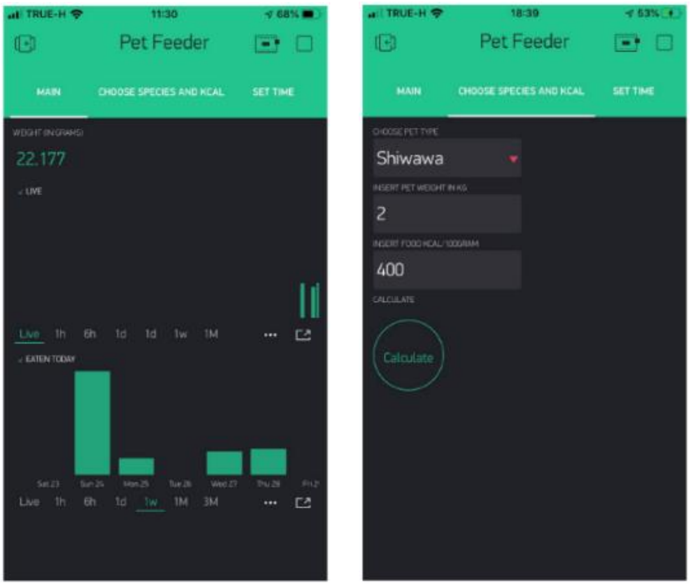
3.4.1. Microcontroller ESP8266

An electronic board called NODE NodeMCU ESP8266 is built around the ESP8266 chip. The microcontroller and internet connection (Wi-Fi) may both be operated by the NodeMCU ESP8266. It is possible to create NodeMCU ESP8266 apps for IoT projects that monitor and control data.

3.4.2. Blynk software

Android Blynk software was used to create software design. This program has five sections that show the time, date, weight of food, and leftovers. The numbers in the five boxes are sensor readings posted to the Blynk cloud service using an Arduino UNO R3.

A pet feeder is a device designed to automatically dispense food to pets, ensuring they are fed at scheduled times even when their owners are not present. Figure 2(a) shows the daily feeding quantity of food in a dog cage graphically. Figure 2(b) represents the pet data, including the kind of pet, weight in kilograms, and the amount of food computed for each meal in a dog cage.



(a) (b)

Figure 2. Blynk application: (a) pet feeder monitoring and (b) pet data

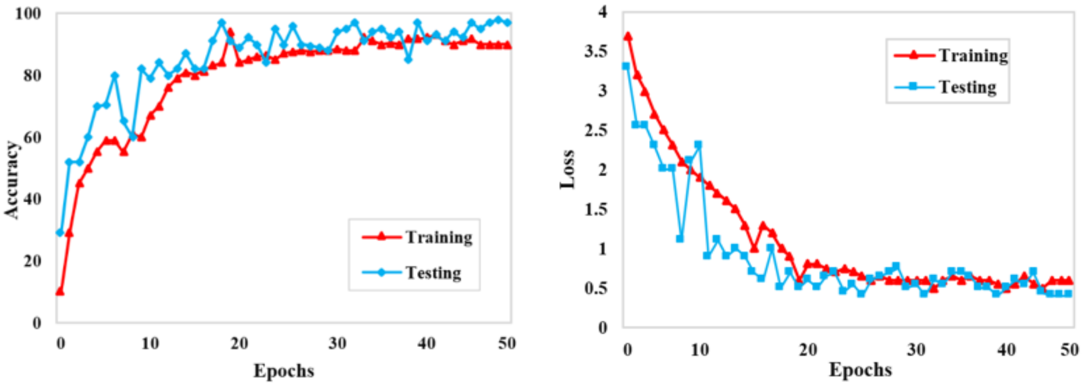
4. RESULT AND DISCUSSION

To determine the overall efficacy of the DL model, assessment metrics and framework testing are required. Accuracy, recall, accuracy, and F1 scores were calculated to compare the overall efficiency of the suggested approach.

The variation in accuracy and loss with enhancing epochs is shown in Figure 3(a) and 3(b). As the no. of iterations enhances on the training set, accuracy increases continuously and the loss value decreases. Less than ten iterations produce testing set accuracy and loss values that are comparable to those on the training set. As shown in Figure 4, the value of the proximity sensor correlates to the closeness of the nearest item. In contrast to the other sensors, this causes the y-axis to be inverted. The sensor value falling below the distance threshold indicates activation. The temperature readings obtained at different points in time are displayed in Figure 5. Based on the emission of monochromatic infrared light, the sensor gathers data. A sensor that was constructed was used to read the data.

Figure 6 represent the classification result to examine the efficiency of the suggested with existing frameworks. The accuracy achieved by ResNet, AlexNet, DenseNet, and proposed pet feeder is 89%, 90.34%, 94.39%, 89.92%, and 99.5%, respectively. The comparison demonstrates the suggested framework performs better than the existing methods. Figure 7 demonstrates the 4-fold classification confusion matrix of the suggested methodology. From this confusion matrix, the proposed has a lower error rate with high classification accuracy in identifying dog near the food and dog away from the food. According to the results, the proposed pet feeder achieves a categorization acc. Table 1 illustrates the accuracy comparison of the suggested model with the existing models.

The time interval that elapses between submitting a request packet to a service and receiving its first response packet is known as the response time. This leads to longer completion times and higher response times. As a result, the food will not be wasted and the dog will get its food on time. Figure 8 shows the response time, which is reduced by 62.65%, 57.14%, and 50% compared to the CMFSVI, petification, and GSM/GPRS, respectively. The suggested Deep-Feed model performs better than the existing models by responding more quickly.



(a) (b)

Figure 3. Performance based on training and testing sets: (a) variation in accuracy with epochs and (b) variation in loss with epochs

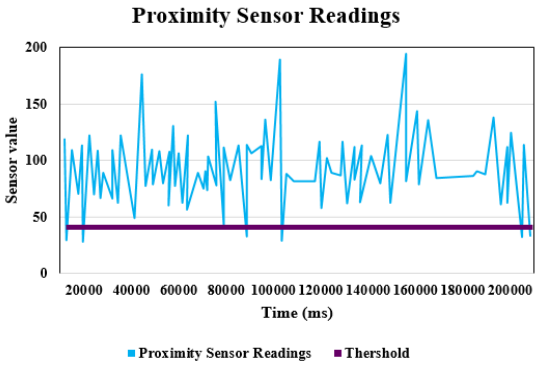


Figure 4. Proximity sensor reading

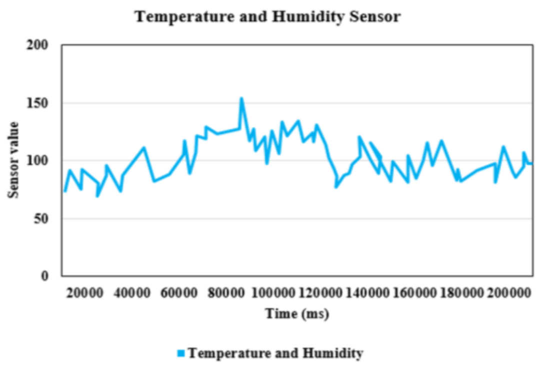


Figure 5. Temperature and humidity sensor

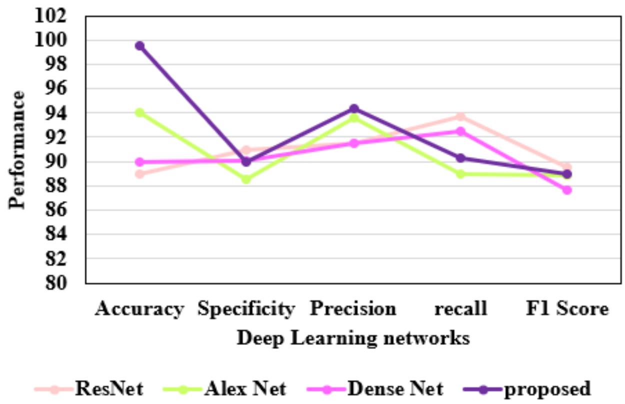


Figure 6. Comparison analysis of existing deep learning models

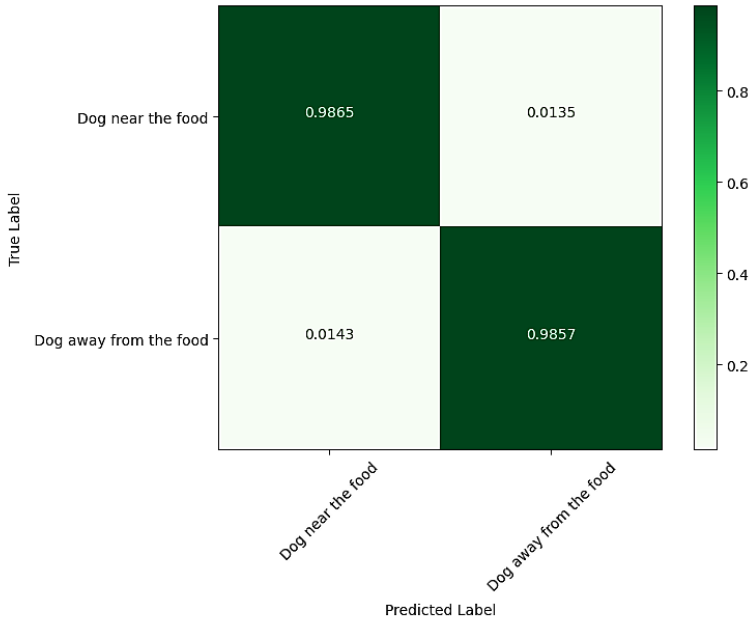


Figure 7. Confusion Matrix

Table 1. Comparison between suggested and the existing models

Methods	Accuracy
CMFSVI [21]	84.9%
Petification [23]	87.58%
GSM/GPRS [20]	93.91%
Deep feed (proposed)	99.5 %

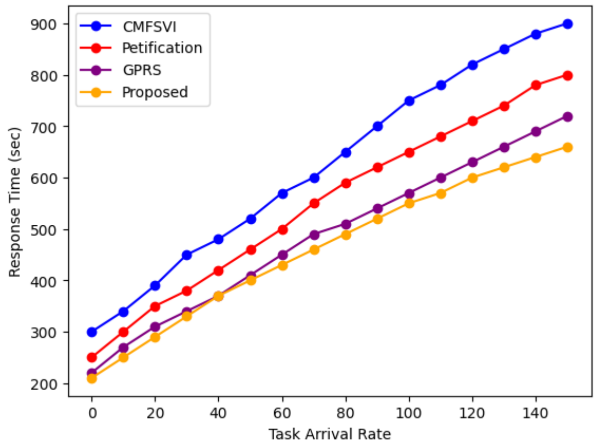


Figure 8. Response time

4.1. Statistical analysis

A paired t-test examines the means of two associated groups to see if they are significantly different from each other. Conduct paired t-tests between the proposed Deep-Feed technique and each existing method such as CMFSVI, petification, and GSM/GPRS to confirm if the reduction in response time is statistically significant. A p-value < 0.05 suggests that the proposed Deep-Feed technique has a significantly lower response time compared to the other method being tested.

5. CONCLUSION

In this research, a novel deep learning-based pet feeding system has been proposed (Deep-Feed) for identifying the food in a cage. The proposed system utilizes pre-processed techniques, including lowering casing, tokenization, lemmatization, and stop word removal, to prepare text data for analysis. CNN is employed for image classification, and BiGRU to predict the dog's behavior. The accuracy of the proposed technique can be as high as 99.95%, while that of traditional models like the CMFSVI, petification, and GSM/GPRS is 84.9%, 87.58%, and 93.91%, respectively. Compared to existing techniques, the proposed Deep Feeder shows better results in terms of Accuracy. Eventually, we hope to find a suitable fusion model and broaden the behavior categories to improve dog behavior recognition accuracy.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

INFORMED CONSENT

I certify that I have explained the nature and purpose of this study to the above-named individual, and I have discussed the potential benefits of this study participation. The questions the individual had about this study have been answered, and we will always be available to address future questions.

ETHICAL APPROVAL

My research guide reviewed and ethically approved this manuscript for publishing in this journal.

DATA AVAILABILITY

Data sharing is not applicable to this article as no datasets we regenerated or analyzed during the current study.

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