Real-Time Threat Prevention System for Mitigating Intrusions by Dogs in Livestock Farming using IoT and Machine Learning

Aekarat Saeliw [1], Watcharasuda Hualkasin [1], Supattra Puttinaovarat [1]

[1] *Faculty of Science and Industrial Technology, Prince of Songkla University, Surat Thani Campus, Surat Thani, Thailand*

***Abstract* – One of the challenges encountered by farmers engaged in livestock farming is the menace posed by stray or ownerless dogs, causing harm to the animals being raised on the farm. This not only adversely affects the health of the animals but also impacts the overall cost associated with their upbringing. Consequently, this research introduces the development of a sophisticated system aimed at preventing threats and intrusions by dogs that pose harm to farm animals. The system leverages Internet of Things (IoT) technology and employs Machine Learning algorithms, specifically Convolutional Neural Network, for real-time tracking and monitoring. The research findings reveal that the developed system demonstrates a high level of efficiency, swiftly and accurately classifying animals entering areas equipped with cameras, achieving an impressive accuracy rate of 92.54%. Furthermore, the system is equipped to promptly notify users and emit deterrent sounds to repel dogs entering the monitored area, enhancing its effectiveness in safeguarding livestock and optimizing farm management practices.**

***Keywords* – Dog classification, deep learning, IoT, mobile application.**

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Corresponding author: Supattra Puttinaovarat,
Prince of Songkla University, Surat Thani Campus, Surat Thani, Thailand
Email: supattra.p@psu.ac.th

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1. Introduction

In regions where the primary source of income is derived from the agricultural sector, a crucial occupation is livestock raising [1], [2], [3], which involves the cultivation of economically significant animals, notably quadrupeds like sheep and goats, and encompassing pigs, cattle, buffalo [4], [5], and avian species such as geese and chickens [6], [7]. Engaging in animal husbandry is recognized as a profession that generates substantial income for farmers. Nevertheless, participants in the livestock-raising profession confront notable challenges, including but not limited to health issues, injuries, and the mortality of animals within their care on farms [8], [9], [10].

Based on an extensive examination of pertinent literature and research, encompassing an exploration of challenges within the Thai context, a common cause of injuries and fatalities among farm animals has been identified—dog bites, particularly those inflicted by stray or ownerless dogs, affecting animals such as goats and sheep [11], [12], [13], [14]. In instances where domesticated animals suffer injuries or perish due to dog bites, there exists a notable absence of avenues to seek compensation for damages or incurred treatment costs, resulting in substantial livelihood losses for farmers. Furthermore, even when the dog responsible is owned, the process of filing a claim for damages is protracted. Current strategies employed to mitigate and address these challenges involve the construction of animal pens adhering to standardized specifications and the assignment of personnel for continuous monitoring. Technological interventions, including the deployment of surveillance cameras, are prevalent in larger animal farms endowed with significant capital and a readily available workforce [15], [16]. However, for small-scale farmers with limited financial resources, reliance on self-implemented surveillance methods persists, often involving the farmers themselves or their family members.

This approach, however, is constrained by its inability to ensure continuous monitoring. The advent of Internet of Things (IoT) and Digital Image Processing (DIP) technologies has demonstrated their efficacy, as they find application in various domains to support, facilitate, and resolve diverse challenges [17], [18], [19], [20], [21].

Based on a comprehensive review of literature and research concerning the integration of IoT (Internet of Things) and DIP (Digital Image Processing) in the management of animal husbandry, particularly to mitigate threats posed by dogs to farm animals, two distinct approaches have emerged. The first involves the application of machine learning image processing techniques for the classification of various animal types [22], [23], [24], [25], [26]. This method exhibits the capacity to differentiate animals within digital images, with accuracy levels contingent upon factors such as classification techniques employed, and the volume of data used to construct the model. Notably, the utilization of deep learning, supported by comprehensive and highly accurate training data, achieves accuracy rates surpassing 90% [23], [25]. Nevertheless, relying solely on machine learning techniques lacks real-time surveillance and tracking capabilities, prompting efforts to address these limitations by advocating for the combined use of IoT and machine learning for animal detection and monitoring across diverse applications [27], [28], [29], [30], [31]. The strengths of the latter method include the ability to monitor animal movement and appearance data in real-time, providing highly accurate results and facilitating real-time notifications to users through various formats such as SMS and application alerts. However, critical analysis reveals persistent limitations, notably the lack of mobile device support, rendering the system inconvenient and restrictive in terms of ubiquitous usage. Additionally, the absence of sound-based techniques for animal control necessitates physical intervention by individuals in the event of encroachment, particularly when users are situated at a considerable distance from the farm location. Consequently, this research addresses these shortcomings by proposing the development of a system that employs IoT and machine learning to prevent threats or intrusions by dogs into the animal farm area. The system notifies users through Line notification in the event of a dog entering the designated area and can emit sounds to repel dogs, thereby alleviating existing constraints. The prototype system is designed to equip farmers in livestock management with effective tools to prevent and address issues related to dogs biting or attacking animals in an efficient and timely manner.

2. Related Works

This research entails a comprehensive investigation and review of pertinent literature and research focusing on issues pertaining to the integration of IoT technology and digital image processing with machine learning. The study is structured into two main components: the application of machine learning in processing image results for animal classification and the utilization of IoT in conjunction with machine learning for monitoring and tracking animals through data from sensors and cameras, processed with machine learning algorithms to classify animals. In the first part of the literature review, the utilization of IoT in animal farming is explored, employing Raspberry PI for automated animal feeding and monitoring various health parameters such as heart rate and body temperature. Notably, the data is presented through a user interface, facilitating tracking, but limitations include the absence of notifications and the omission of results evaluating the model accuracy [27]. Subsequently, the use of IoT combined with machine learning techniques, specifically artificial neural network (ANN) algorithms, is presented for detecting pets on roads to prevent vehicular accidents. While the research enables notifications through a computer, limitations include the absence of a universally applicable application and the lack of presented accuracy evaluation results [28]. Another study integrates IoT with digital image processing (DIP) for monitoring animals that destroy agricultural crops, utilizing cameras and Rasberry Pi. Although the system can monitor such animals, the accuracy of detection has not been reported [29]. Furthermore, the use of IoT and deep learning is proposed to detect animals and issue warnings to prevent crop destruction in agricultural areas. Limitations include the lack of an application, restricting result viewing to the sensor set screen, and the absence of presented accuracy evaluation results [30].

Additional research focuses on developing an application for detecting and classifying four types of animals (elephant, leopard, gaur, and bear) using MATLAB and deep learning techniques, achieving a classification accuracy between 95.90% and 97.94%. Notably, the ability to notify via SMS is highlighted, while limitations include the absence of sound for repelling animals, necessitating physical intervention [31]. The use of IoT in recording images to identify animals using deep hybrid neural networks is proposed, boasting an accuracy of 99.6%. While exhibiting high classification accuracy, limitations include the absence of an application for user notifications [32].

Another study proposes animal monitoring along railway lines using IoT combined with deep learning, achieving a classification accuracy of 99.91% [33]. Additionally, the application of IoT and deep learning for monitoring animals in the wild is presented, utilizing hardware such as Raspberry Pi and cameras. Limitations are unspecified [34]. Lastly, the use of IoT and machine learning to detect animals and prevent agricultural land and crop damage is discussed, with a classification accuracy ranging from 85% to 85.89% [35].

In the second part, employing machine learning for the classification of animals, a method utilizing convolutional neural network (CNN) techniques was identified for the classification of dogs and cats. This method involved the creation of a model based on data derived from 1,000 images. The accuracy evaluation results revealed a precision and recall value of approximately 45%, indicating a limitation as the accuracy remains relatively low [22]. Another approach proposed image classification to differentiate between cats and dogs using deep learning techniques, yielding an accuracy evaluation of 92.70% [23]. Furthermore, the classification of cats and dogs was presented using CNN in comparison with machine learning techniques such as support vector machine (SVM) and CNN. The accuracy evaluation results indicated a precision of 92.49% [24].

Digital image classification was introduced to distinguish between cats and dogs using deep learning with the VGG model algorithm. The accuracy evaluation results indicated a high accuracy of 98.56% for the training data and 84.07% for the testing data [25]. Additionally, the classification of digital photographs to discern various groups of dog species employed various deep learning algorithms. The accuracy evaluation revealed that the Inception ResNet V2 algorithm achieved the highest accuracy, ranging from 88.40% to 93.30% [26]. Another application focused on digital photo classification to distinguish dog breeds using deep learning, demonstrating an accuracy of 89.92% [36]. Lastly, digital photo classification was presented for distinguishing between cats and dogs using CNN, achieving an accuracy of 93.67% for the training data and 90.10% for the testing data [37].

Upon an extensive review of the literature and related research in both parts, it is evident that previous studies are encumbered by noteworthy limitations. Notably, a prevailing constraint is the absence of a developed system or application, rendering it impossible to provide notifications consistently and universally across various locations. Additionally, these systems often lack compatibility with mobile devices and fail to support real-time notifications.

Moreover, the incapacity to emit sounds for repelling dogs or other animals is a recurrent limitation. Furthermore, certain studies have omitted the presentation of accuracy assessment results, thereby diminishing the comprehensiveness of their findings. In response to these identified limitations, this research seeks to contribute by addressing and ameliorating these deficiencies. The primary objective is to develop and enhance systems that facilitate continuous tracking and monitoring of dog invasions and attacks on farm animals or within animal holding facilities. Through these advancements, the research endeavours to provide a more comprehensive and effective solution to the challenges identified in the existing literature.

3. Methodology

This research employs a combination of hardware and software to construct the system, and the implementation details are meticulously outlined in Table 1 for both server and client components. The architectural or conceptual framework proposed in this research is illustrated in Figure 1. The circuit design specifications of the system are bifurcated into two main parts: Arduino and Raspberry Pi.

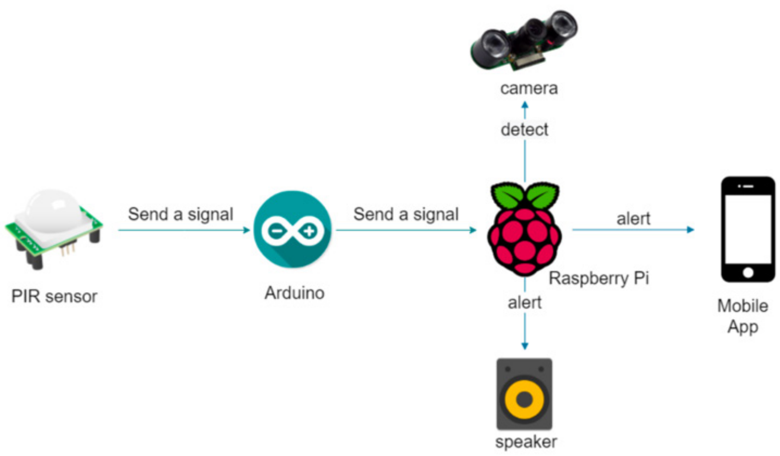

Figure 1. Conceptual framework

Table 1. Hardware and software

Topic	Client	Server
Hardware	- Smartphone - Microcomputer	- Arduino Uno - Raspberry Pi4 - Raspberry Pi Night Vision 5 MP - Passive Infrared (PIR) Sensor - Speaker - Microcomputer
Software	- Android - IOS - Line	- Windows 10 or upper - Visual Studio Code - Arduino DIE - TensorFlow - Python - Firebase
Network	- 4G/5G - Wi-Fi	- Dual 100 Mbps - Wi-Fi

Within the Arduino circuit, a passive infrared sensor (PIR) is initially connected and subsequently linked to the Raspberry Pi. The Raspberry Pi circuit encompasses connections to the camera module, speaker, and transmission of data to the mobile application. The Raspberry Pi serves as a command unit for various devices, functioning as a medium for transmitting data and diverse signals activated by the movement or passage of living entities. In the region where the camera is installed, the sensor emits a signal to the Arduino, which receives the value from the PIR sensor, processes the signal as an open or closed light indicator, and transmits this signal information to the Raspberry Pi.

Upon receiving information from the Arduino, the Raspberry Pi commands the camera module to capture images and forwards them to the Raspberry Pi for image processing. Machine learning algorithms are employed to classify the images as either dogs or non-dog, with the results stored in a database. Simultaneously, notifications are dispatched to the user, and dog-repelling sounds are emitted through the integrated speakers in instances where the classification outcome indicates the presence of a dog.

3.1. System Analysis and Design

The system analysis and design in this research employ use case and class diagrams, as depicted in Figures 2 and 3. Examination of these figures reveals that users have the capability to access notification information through Line notification when dogs enter the designated camera-installed area. Additionally, the system emits dog-repelling sounds through speakers situated in the farm area where both cameras and speakers are strategically positioned. The operational sequence of the system preceding notification involves motion detection, capturing moving entities, and subsequent image processing for classification into categories of dogs or non-dogs.

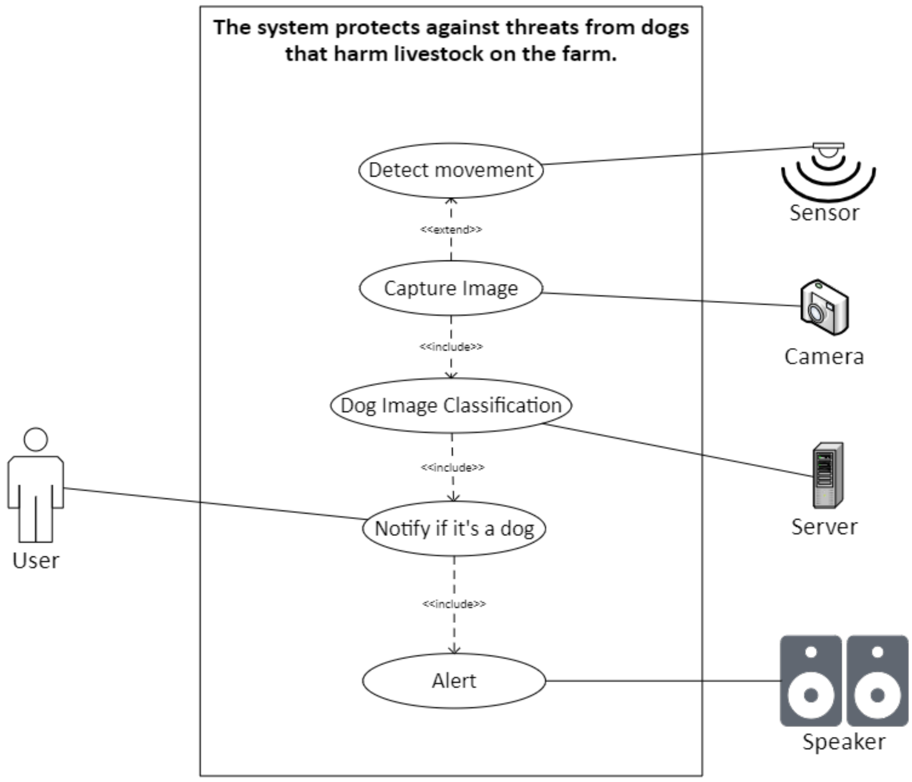

Figure 2. Use case diagram

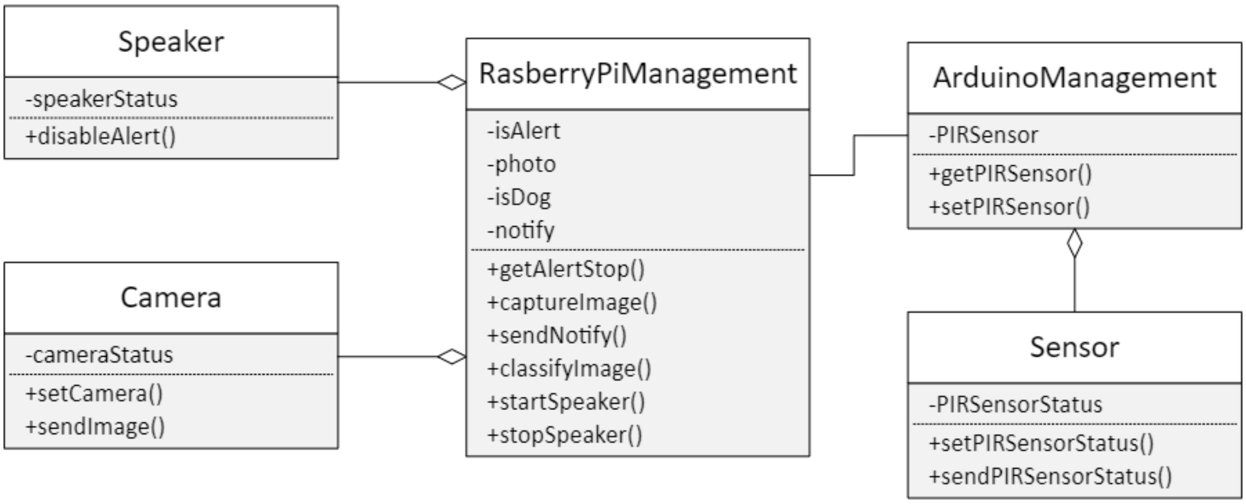

Figure 3. Class diagram

3.2. Digital Image Classification

In the domain of digital image processing, the classification of moving objects captured by cameras is conducted through the utilization of models crafted with machine learning techniques, employing algorithms known for their high accuracy. Within the scope of this research, four distinct algorithms, namely support vector machine (SVM), k-nearest neighbors (KNN), random forest (RF), and convolutional neural network (CNN), were selected for model development. A comparative assessment was executed to gauge the accuracy of the models generated through these four algorithms. The model creation in this study involves a binary classification into two classes: dog and non-dog. The training dataset comprises a total of 25,018 images, evenly divided between the dog class (12,509 images) and the non-dog class (12,509 images). For the testing phase, the dataset is systematically partitioned using the 10-fold cross-validation method, resulting in ten distinct groups derived from the training data. Furthermore, a separate validation dataset consisting of 402 images is employed for testing, with an equitable distribution of 201 images allocated to each of the dog and non-dog classes.

3.3. Accuracy Assessment

The assessment of accuracy in digital image classification, specifically in distinguishing between dogs and non-dogs within this research, was conducted utilizing calculation methods such as accuracy, precision, recall, and f-score. This evaluation entailed a comparative analysis between the outcomes produced by the classification model and the classifications assigned to real images through manual annotation.

4. Results

The research outcomes are categorized into three main sections: the results of IoT device connection design, digital image classification outcomes, and the findings from the development of a system to notify users of dog intrusion. The specific research results are as follows:

4.1. IoT Device Connection Design Results

The design and connectivity of IoT devices are visually presented in Figures 4 to 7. Figure 4 illustrates the connection between the Arduino Uno board and the passive infrared (PIR) sensor, utilized for motion measurement. In Figure 5, the connectivity between the Raspberry Pi 4 and the camera module (Raspberry Pi Night Vision 5 MP model) is depicted for monitoring and image capture. Figure 6 demonstrates the interconnection between the Raspberry Pi 4 and Arduino Uno, facilitating mutual communication. Figure 7 showcases the device utilized for detecting and emitting dog-repelling sounds. These visual representations elucidate the configured components forming the IoT system.

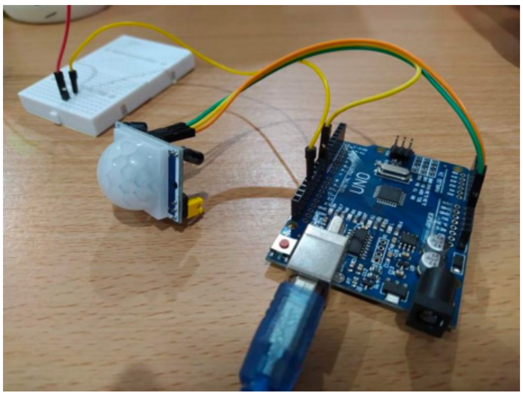

Figure 4. The Arduino Uno board and the PIR sensor

Figure 5. The connectivity between the Raspberry Pi 4 and the camera module

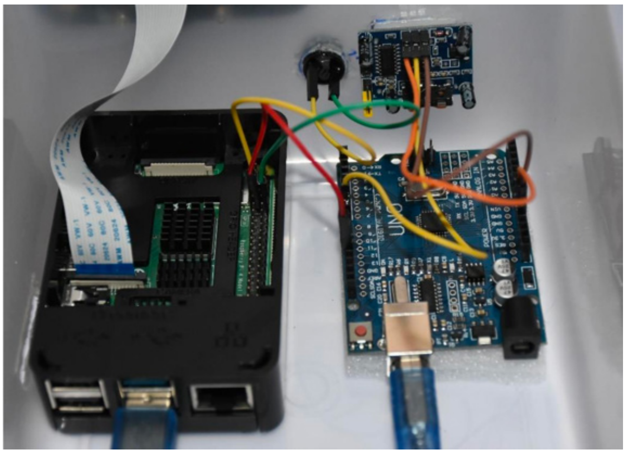

Figure 6. The interconnection between the Raspberry Pi 4 and Arduino Uno

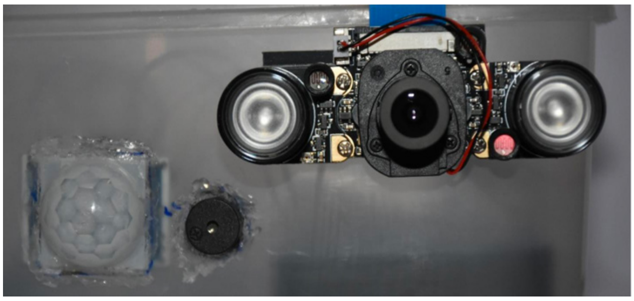

Figure 7. The device utilized for detecting and emitting dog-repelling sounds

4.2. Digital Image Classification Results

The outcomes of digital image classification in discerning between dogs and non-dogs in this research were subjected to a comparative analysis employing four machine learning algorithms: SVM, KNN, RF, and CNN. Evaluation of accuracy revealed that the CNN algorithm demonstrated the most precise classification results, followed sequentially by KNN, RF, and SVM. Comprehensive details of the accuracy evaluation, encompassing accuracy, precision, recall, and f-score metrics, are presented in Table 2 and graphically represented in Figure 8. The evaluation methodology in this section employed the 10-fold cross-validation approach.

Table 2. Accuracy assessment

Algorithms	Accuracy	Recall	Precision	F-Score
SVM	87.48%	87.48%	87.75%	87.62%
KNN	95.72%	95.72%	95.78%	95.75%
RF	94.98%	94.98%	94.99%	94.99%
CNN	97.12%	97.12%	97.12%	97.12%

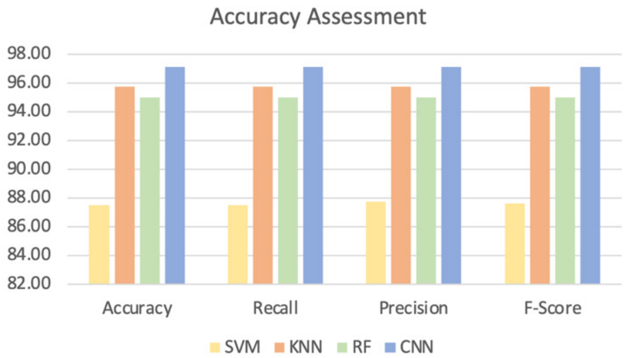

Figure 8. Accuracy assessment

Furthermore, an additional accuracy assessment was conducted utilizing a validation dataset comprising 402 images, segregated into 201 images for the dog class and 201 images for the non-dog class. The algorithm yielding the most accurate evaluation results was assessed using this validation dataset. The results indicated an accuracy value of 92.54%, precision of 92.54%, recall of 93.27%, and an f-score of 92.90%. Despite a decrement in accuracy value for the validation data compared to the training data, a detailed analysis revealed that the majority of misclassified images pertained to non-dog entities. This, however, does not impede the efficacy of monitoring dogs entering farm or animal-raising areas. Focusing solely on the classification of dog-related instances, the accuracy was found to be 99%. Exemplary instances of classification within the dog class are illustrated in Figures 9 and 10, while those within the non-dog class are depicted in Figures 11 and 12. Figures 9 and 10 demonstrate the accurate classification of dogs, indicating a higher probability of belonging to the dog class than the non-dog class. Conversely, Figures 11 and 12 illustrate correct classification outcomes for non-dog entities, such as cats and people. Consequently, the model developed utilizing the CNN algorithm exhibits potential utility in classifying dogs to prevent them from causing harm to pets.

Figure 9. Dog classification result

Figure 10. Dog classification result

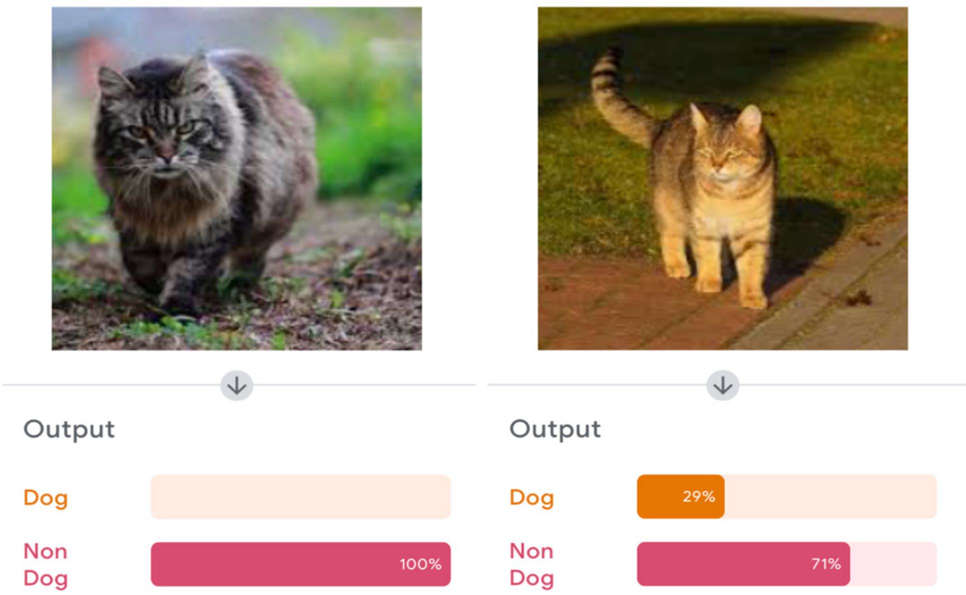

Figure 11. Non-Dog classification result

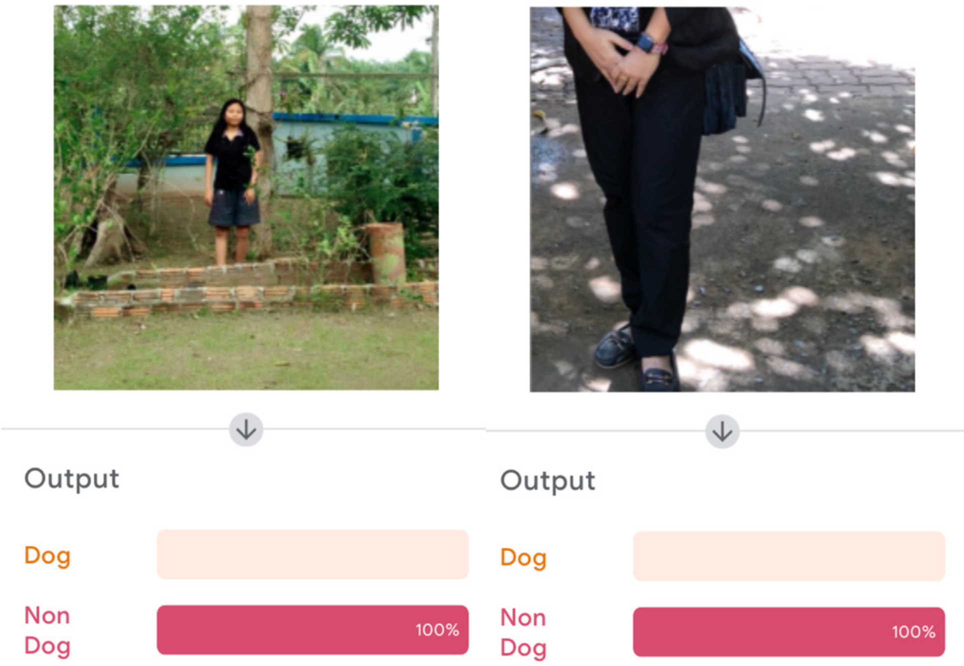

Figure 12. Non-Dog classification result

4.3. System Development Results for Dog Intrusion Notification

The outcomes of the notification system development targeting users or farmers are detailed in this section. This module is designed to activate when a dog enters the region under surveillance by the camera. Upon the detection and processing of an image, a notification is dispatched in the form of a message through Line notification. Importantly, users are not constrained to the proximity of the computer, as illustrated in Figure 13. Should the user opt to access the application on the computer, images capturing instances of dogs entering the camera-installed area can be reviewed, as exemplified in Figure 14. This development empowers users with the capability to engage in real-time monitoring, eliminating limitations associated with time and location.

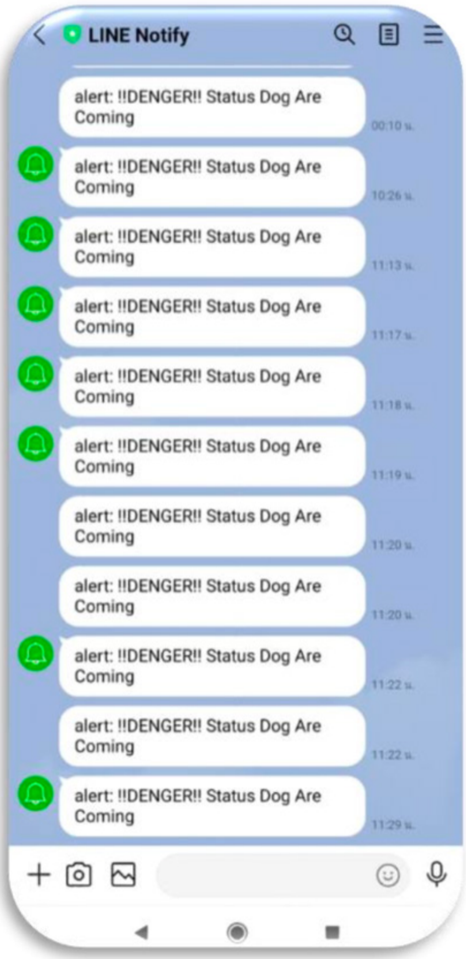

Figure 13. Line notification result

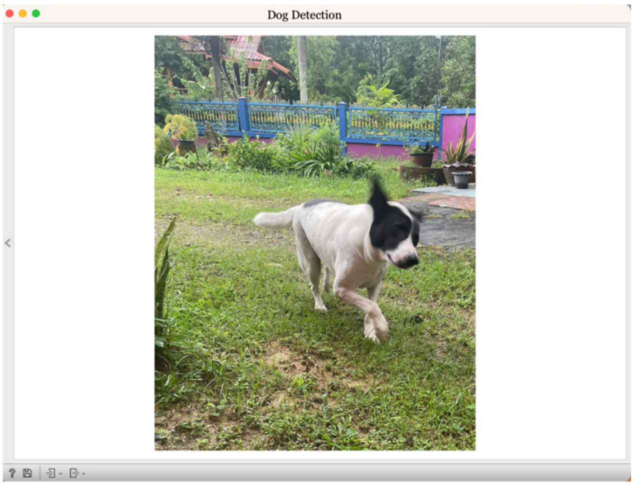

Figure 14. Classification result in application

5. Discussion

The outcomes of the system development expounded in this research hold significant implications for encouraging farmers or users to proactively monitor and track the ingress of dogs into farm areas, thereby mitigating the issue of dogs attacking farm animals. The developed system facilitates real-time notifications, distinguishing itself by leveraging deep learning algorithms, specifically CNN, with an accuracy exceeding 90%. This achievement aligns with findings from prior studies [23], [24], [26], [31], [32]. Moreover, the system's notification mechanisms, whether through applications or Line notification, are consistent with previous research on application and SMS notifications [28], [31]. The integration of IoT with deep learning in this study aligns with earlier research supporting enhancements in notification systems [31], [32], [33], [34], [35]. Notably, a key distinction is observed, as much of the extant research has yet to progress into application development [28], [32]. Analysing the limitations of prior research relative to the developments presented in this study, noteworthy improvements are evident. The proposed system surpasses previous limitations by ensuring continuous and universal notifications, compatibility across diverse devices, support for real-time notifications, and the ability to emit sounds to repel dogs. The research results demonstrate high accuracy in dog classification, affirming its utility for real-time tracking and monitoring of dog encroachments and attacks on farm animals or animal holding facilities. This, in turn, contributes to the more efficient support and advancement of farmers in their animal-raising endeavours.

6. Conclusion

This research contributes to the field through the design and development of a system aimed at preemptively addressing threats or incursions by dogs that pose harm to farm animals. Leveraging IoT and deep learning technologies, the system operates in real-time, ensuring a high level of accuracy. It is equipped with the capability to promptly notify users, enabling them to conduct timely inspections and manage issues within the farm area. Additionally, the system incorporates an auditory feature designed to repel dogs from the area, thereby mitigating the risk of canine attacks on farm animals. The system's versatility extends to potential applications in other research domains, such as the monitoring of animals that may pose threats to agricultural crops and surveillance in various high-risk environments. Consequently, farmers can utilize this system as a supportive tool in their operational endeavors.

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