An Internet of Things (IoT)-based Veterinary Support System for Livestock Skin Disease Health Care using MobileNetV2

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Abstract. In this work, we present a novel approach for the early detection and diagnosis of skin diseases in farm animals, a major concern that can lead to reduced productivity, decreased animal welfare, and economic losses. Using Internet of Things (IoT) and MobileNetV2, we have developed a system that is built using Raspberry Pi for the gateway and low-power ESP 32 microcontrollers for sensor attachment. This system consists of sensors placed on the animals' bodies, including an electrocardiogram (ECG) sensor and a DS18B20 temperature sensor, which continuously monitor the animals' vital signs and skin temperature. The collected data is transmitted to a central server where it is processed using MobileNetV2, a deep learning model trained to recognize three common skin diseases in farm animals: Dermatophilosis, Dermatophycosis, and Papillomatosis. The results of this processing are then made available to animal owners and farmers through a mobile app. Our results show that the proposed system can accurately detect and diagnose skin diseases in farm animals with a high degree of recall (0.96), precision (0.96), and f1 score (0.96). The use of IoT and machine learning allows for real-time monitoring and early detection of skin diseases, which can significantly reduce the spread of infection and improve the overall health and welfare of farm animals. In addition, the system is intended to support veterinarians in assessing the health status of farm animals. Overall, this work demonstrates the potential of using IoT and machine learning for the early detection and diagnosis of skin diseases in farm animals and highlights the importance of continuous monitoring and proactive management in maintaining the health and welfare of these animals.

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1 Introduction

Livestock production plays a crucial role in global food security, particularly in Africa, where a significant proportion of the continent is conducive to animal agricultural production due to its historical experience and available resources. However, animal diseases can pose a significant threat to livestock production, with over 20% of losses being attributed to these diseases [1].

In addition, many emerging animal diseases can be transmitted to humans, making it essential to address and prevent these diseases in animal populations [2]. To address these challenges, it is necessary to continuously monitor the health of animals and accurately diagnose and treat any unhealthy animals as early as possible. The use of technologies such as the Internet of Things (IoT) and artificial intelligence can assist veterinarians in this effort. In addition, veterinarians face various challenges in their practices, including client concerns, changing practices, staff management, and availability, which can impact their ability to effectively diagnose and treat animal diseases [3].

This study presents a support system for veterinarians that aims to improve their diagnostic and treatment planning capabilities, using a combination of literature review, fundamental concepts, and methodology. The use, results, and evaluation of the system are also analyzed in this paper, which is structured into five sections. Section 1 introduces the need for the system, while sections 2 and 3 provide a review of the fundamental concepts and methodology used in its development. The final two sections of the paper focus on the use and evaluation of the system, as well as the results obtained.

2 Review of fundamental concept

Livestock agriculture is basically the method of animal breeding for consumption purposes only. Good animal welfarism requires disease prevention and veterinary [2] treatment, appropriate shelter management, nutrition, humane handling.

2.1 Livestock Farming

Livestock agriculture deals with raising and keeping livestock, principally for the drive of producing meat, egg, milk. Figure 1 shows the various farm animals that are majorly reared Livestock agriculture likewise embraces leather and wool production and could comprise of animals reserved for recreation (riding/racing) and draft [3]. Livestock farming is basically the method of animal breeding for consumption purposes only. Animal husbandry, some other word for livestock farming, is a rapidly expanding farming sector in Nigeria, and its productivity is mainly the explanation why more ambitious farmers participate in livestock farming [4] which are of two varieties [5]. In intensive farming schemes, as the livestock are housed and fed, are also basically "landless." Figure 1 shows cattle that are domesticated intensively. These involve livestock and limited ruminant feedlots, zero-grazing dairy production, and indoor or semi-indoor pig and poultry production systems, as well as more common animals such as rabbits and crocodiles. As a result, dairy cattle can be kept on pasture, but calves are raised in indoor systems; dry sows can be kept in large outdoor camps in otherwise fully intensive pig production systems [6].

Fig. 1 Intensive farming system [7]

Fig. 2 Extensive livestock farming [8]

Extensive animal processing is a method of animal farming with low productivity per animal and per land. Compared to the farmland area, it uses small amounts of inputs, capital, and labor. The idea of pastoralism is often correlated with large-scale animal production. Many grazing livestock systems that feed on permanent grasslands shown in figure 2 can also be called comprehensive livestock systems where grass valuation is achieved by grazing and very little use of inputs, labor and capital [9].

The development of a monitoring system in figure 3 [11], is needed for ranking the welfare state of small ruminants at farm level. The assessment of welfare at farm level could be used to quantify the impact of different husbandry conditions on animals, but it could be also used for legislative requirements, as a certification system and as an advisory and management tool by farmers [10].

Fig. 3 Wireless sensor networks for IoT [11]

2.2 Internet of Things

Gartner [12] predicted the internet of things (IoT) would have at least 8.4 billion connected "things" in use, rising to more than 20 billion by 2020. A key factor likely to add to this growth is an emerging smart-sensor movement giving birth to the Internet of Animals with potentials to change the way we approach animal husbandry pet ownership & veterinary practices [13].

2.3 Veterinary Support System

Consumer -grade health and activity trackers are being applied to veterinary patients and helping in generating veterinary informatics which will help in meaningful diagnosis of behavioral health issues [13].

Sensors usage has made provision for detailed history that could not be obtained in the typical consultations [14]. Recovery of animal post-surgery or following medication can be measured enabling quicker follow-up where needed, providing a standard of care as a result. Thus, informed decisions are made.

As we live on internet, veterinarians believe there is a strong desire for mobile technology in veterinary medicine and the use of this technology will allow them to practice more effectively. Results showed in [15] that mobile devices are prevalent and widespread among veterinarians with more than sixty percent surveyed strongly agreed mobile technology will advance patient care, client communication, and improve access to clinical data and medical literature.

2.4 MobileNetV2

The MobileNetV2 has been proposed to be used in this work as the base model for the skin disease identification is a convolutional neural network (CNN) designed for efficient image classification and object detection. It was developed to run on mobile devices and other resource-constrained systems, hence the name "MobileNet".

MobileNetV2 is based on an inverted residual structure, where the input and output of the residual block are thin bottleneck layers, and the intermediate layers are expanded to match the dimensions of the input and output layers [16]. This structure allows the network to learn more complex features using fewer parameters and computation, making it more efficient than traditional Convolutional Neural Networks (CNNs).

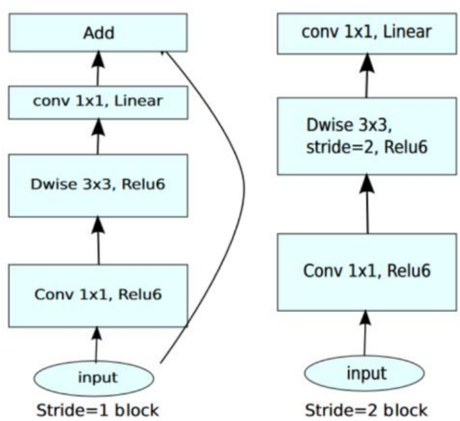


Fig. 4 Architecture of MobileNet V2 [16]

MobileNetV2 also uses depthwise separable convolutions, which split the standard convolution operation into two separate operations: a depthwise convolution and a pointwise convolution.

Reference to fig 4, the depthwise convolution applies a single filter to each input channel, while the pointwise convolution combines the outputs of the depthwise convolution using a 1x1 convolution. This separation reduces the number of parameters and computations, further improving the efficiency of the network.

$$\mathrm{ReLU} : \mathrm{f(x)} = \max(0, x) \tag{1}$$

In addition to its efficient structure, MobileNetV2 also uses batch normalization and ReLU activation functions used in equation above to improve the convergence of the network [17]. Batch normalization helps to standardize the activations of the network, while ReLU helps to introduce nonlinearity, allowing the network to learn more complex features.

3 Methodology

3.1 System Implementation

The system developed is a synergy of software and hardware components. Before development of the system research on case scenario on how it can used was looked upon in advent of different ailment. Also, finding as shown that there are key indicators which are germain to the well being of the animal [18]. Some of these parameters are the rumination, pulse/heart rate, respiratory rate, temperature. One or more of these parameters alteration's in status quo might be symptoms to some diseases. In the case of heat exhaustion in which results in panting (increased respiration rate) with increased temperature but in case of salmonellosis (scours) together with other symptoms which results in increased breathing but neither temperature nor heart rate variation are evident. The measurement of these health indicators are important in these work which has brought in the use of electronic sensors.

In the measurement of the heart rate, three methods are looked into which are Photoplethysmography, Phonocardiograph and Electrocardiograph.

The opening and closure of valves in the heart creates noises that are usually detectable though a stethoscope, through contraction and dilation. Such signals are heart beat rhythmic, and can be detected using microphones. Among the regular heart rhythms (S1 and S2-Lub and Dub), it is even possible to capture irregular noises, or murmurs. The heart rhythm is measured using natural heart rhythms. The typical heart tones and multiple murmurs have distinct spectral properties, such that the cardiac irregularities can be visualized through adequate filtering. The acoustic ability is used for assessing heart rate in phonocardiographs [19].

The blood vessels throb during each heart period and transport blood to / from different areas of the human body. As light emission such as infrared in a finger or ear lobe travels into a blood stream, the transmitted light pulse from the finger / earlobe is intermittent and differs owing to both the rhythmic movement and absorption properties of the fluid [20]. The optical variability is employed to produce Photoplethysmographs.

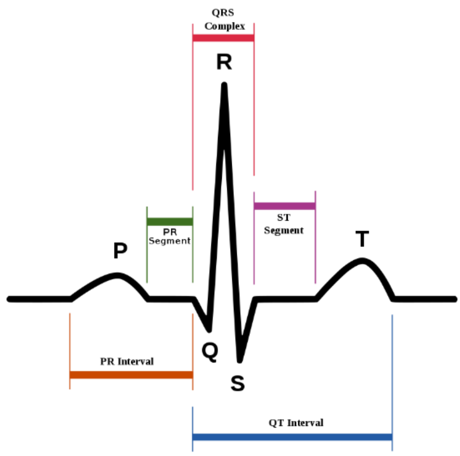


Fig. 5 ECG of a heart in normal sinus rhythm [21]

3.1.1 Electrocardiograph

The activation and relaxing of cardiac muscles allow blood to pump in and out of the heart. In each cardiac process, a community of tissue in the heart called the sino atrial node (a.k.a., heart's pacemaker) produces electrical signals that travel out over the core and induce rhythmic contraction and relaxation of heart muscles. Such electrical impulses may be measured by inserting electrodes in the human body at different locations [22]. An electrocardiogram (ECG) measures this changing electrical impulse, and it shows the actual cardiac rhythm as shown in figure 5. Doctor should test the ECG machine's reported history to search for some cardiac issues which would include:

• Heart rate: Difficulties that comes o with detecting pulses coupled with the irregularities with unusually fast (tachycardia and slow (bradycardia) heart rates are measured correctly by ECG.

• Heart rhythm: Conditions whereby heart's electrical system malfunctions may occur, heart rhythm irregularities (arrhythmias) are shown by ECG.

Some others are showing evidence of previous heart attack, structural abnormal lities and inadequate blood and oxygen supply to the heart. Many methods in [23], [24], [25], [26], [27] have been proposed on deriving breathing rate from ECG.

Breathing rate also identified as respiratory rate are derived from ECG using various algorithm [28] which is termed ECG derived respiration. Visualized in figure 6 are the ECG features used in some 2 EDR algorithms discussed here.

1. As defined by Equation 2, the EDR resulting from the heart rate variability as estimated by the time gap between the R summits in the QRS complex [29].

$$EDR_{HRV}(n) = t_{QRS}(n+1) - t_{QRS}(n) \quad (2)$$

2. A significant correlation exists in the between the QRS amplitude and respiration. Since non-standard QRS-complexes are predicted in the data that are logged and there is a higher reliability in R to S amplitude compared to the R to baseline amplitude [30]. As defined in equation 3, the EDR was estimated as R to minimum value around the R-peaks.

$$EDR_{AMP}(n) = V_R(n) - V_{min}(n) \tag{3}$$

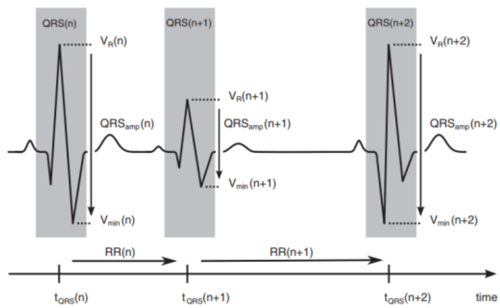


Fig. 6 Employed ECG features in the Algorithm of the EDR [23]

A 3 lead ECG was used in this work and was interfaced to a wifi-protocolled wireless microcontroller.

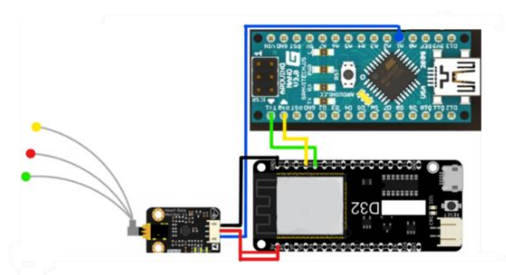


Fig. 7 ECG Circuit Connection

3.1.2 Rectal Thermometry

Only at a certain temperature does the body function properly. In order to insure the processes, operate correctly, the animal body holds itself at a steady temperature in a limited space. For various groups of species, this natural body temperature is variable. The insertion of thermometer into the rectum via the anus to takes the temperature is called Rectal Thermometry. Figure 8 shows the rectal temperature circuitry interfaced with a lolin d32.

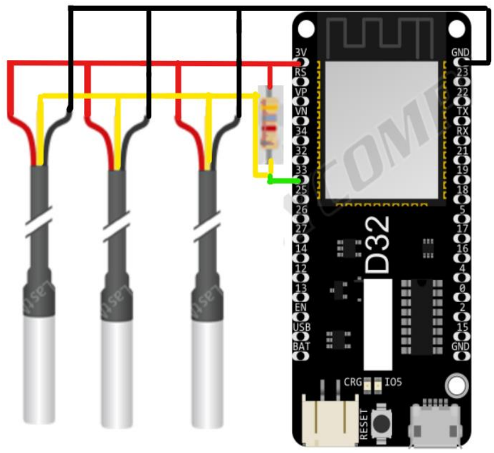


Fig. 8 Circuit Connection for Rectal Thermometry

3.2 System Overview

Fig 9 depicts the overall architecture and setup of this IoT based veterinary system. It shows how the animals physiological parameters are being tracked, monitored and it also shows how the technologies wireless sensor network, IoT are used to achieve a system that renders supports to the veterinarian.

The first phase as shown as phase 1 illustrates the sensors which assembles the physiological data from the animal with which they have contact with. Data are being simultaneously stored locally and transmitted to the cloud server.

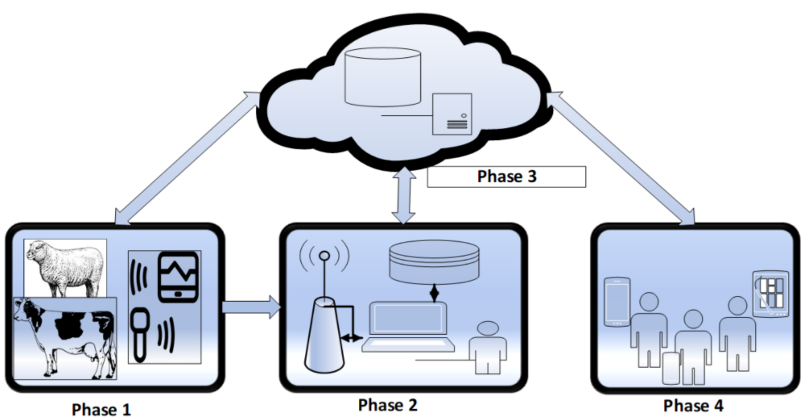


Fig. 9 Architecture of Veterinary Support System

In the second phase of the system, the segment serves as a gateway and communicates with the cloud server to synchronize data. It also displays the current results of analytics based on the animal's state.

The third phase represents the cloud server, which provides global access to the animal's health data, and the fourth phase represents the end users, including the veterinarian, who use the system. The cloud endpoint for the mobilenetV2 model deployed on Azure allows users to identify skin diseases in animals by taking images.

4 Experimental Results

In this study, we developed a model for the classification of skin diseases using Python programming and the Pytorch framework. The model was run on an Azure Linux Virtual Machine with 6 vCPUs, 56GB of RAM, 280GB of temporary storage, and a 12GB NVIDIA Tesla K80 GPU.

In order to generate datasets for the three skin diseases of interest (Dermatophilosis, Dermatophycosis, and Papillomatosis), search terms related to these diseases were used on Google Images and Bing Images. This allowed for the collection of images for each disease, which were then used to train and evaluate the MobileNetV2 model. The use of multiple search engines helped to ensure a diverse and representative dataset for each disease.

4.1 Skin Disease Model Performance Analysis

In this study, we evaluated the performance of our classification model using a variety of evaluation metrics, including precision-recall, F1 score, ROC, lift curve, and cumulative gains graphs.

Fig 10(a) shows the precision-recall graph which plots the precision of the model on the y-axis and the recall on the x-axis, with a diagonal line representing a model that is no better than random chance. In our study, we found that the model had a high precision and recall across all classes, with a precision averaging up to 0.96 and a recall averaging 0.96. These results indicate that the model was able to accurately classify most positive examples, while also minimizing the number of false positive predictions.

Fig 10(b) gives the view of the ROC curve which is a measure of performance for classification tasks at different threshold levels. It indicates how well the model can differentiate between classes by showing the relationship between the true positive rate and the false positive rate. In our study, we found that the ROC curve of the model had a high area under the curve, indicating that it was able to effectively distinguish between positive and negative examples.

The F1 score is a measure of a test's precision and recall and is particularly useful for unbalanced datasets. Shown in fig 10(c), we found that the F1 score of the model has an average score of 0.96. This suggests that the model was able to achieve a good balance between precision and recall

The lift curve in fig 9(d), is a measure of the model's performance compared to random chance. It shows the ratio of the true positive rate of the model to the true positive rate of a random model at each decile of the population. In our study, we found that the lift curve of the model was consistently above the diagonal line, indicating that it was performing better than random chance.

The cumulative gains graph in fig 10(e), is a visual representation of the model's performance in terms of the percentage of positive cases that are correctly classified. In our study, we found that the cumulative gains curve of the model was steep, indicating that it was able to correctly classify a high percentage of positive cases.

Overall, the results of these evaluation metrics demonstrate the effectiveness of the proposed model in classifying the different skin diseases. These findings suggest that the model may be a useful tool for assisting in the diagnosis and treatment of skin conditions. Further studies are done below to confirm the generalizability of these results and to assess the model's performance.

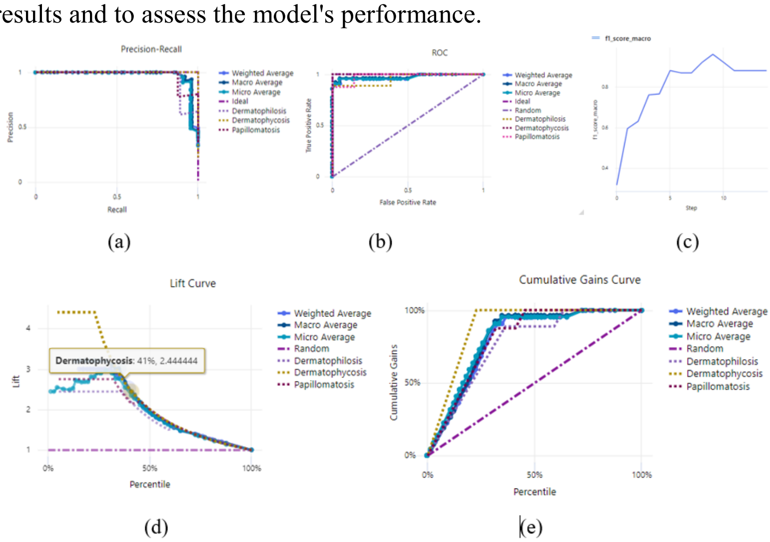
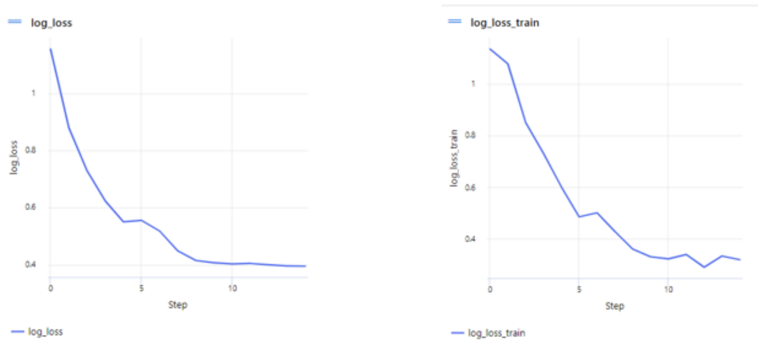


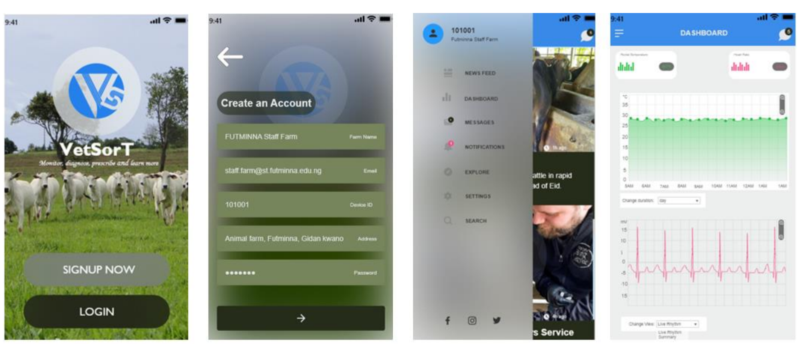
Fig. 10 Multi-Metric Evaluation of Model Performance: Precision-Recall Curve (a), ROC Curve (b), F1 Score (c), Lift Curve (d), Cumulative Gains (e)



(a) (b)

Fig. 11 Training and Validation Log Loss for MobileNetV2 Model for Skin Disease Classification in Farm Animals ((a): Validation Log Loss, (b): Training Log Loss).

In Figure 11, we can see the validation log loss (a) and training log loss (b) for our MobileNetV2 model during the training process. The log loss is a measure of the model's performance, with lower values indicating better performance. From the figure, we can see that the log loss for both the training and validation sets decreases over time, indicating that the model is learning and improving its performance. However, while the training log loss continues to decrease, the validation log loss remains relatively stable, indicating that the model can effectively learn from the training data but may be overfitting to the training data. Once again, the log loss values demonstrate that the MobileNetV2 model is performing well in accurately classifying skin diseases in farm animals.



(a) (b) (c) (d)

Fig. 12 Mobile App for Veterinary Support System: Features and Resources for Farm Animal Owners and Veterinarians

4.2 Results of Implementation and Evaluation of Mobile App for Veterinary Support System

Figure 12 (a, b, c, d) provides an overview of the various features and resources available within the mobile app for the veterinary support system, including the landing page, the sign-up page, the menu page, and the data chart page. These figures offer a detailed description of the app's functionality and illustrate the range of resources and tools available for farm animal owners and veterinarians to manage the health and well-being of their animals. The landing page serves as the home page of the app and provides an overview of the app's features and benefits. It includes a login button for existing users and a sign-up button for new users.

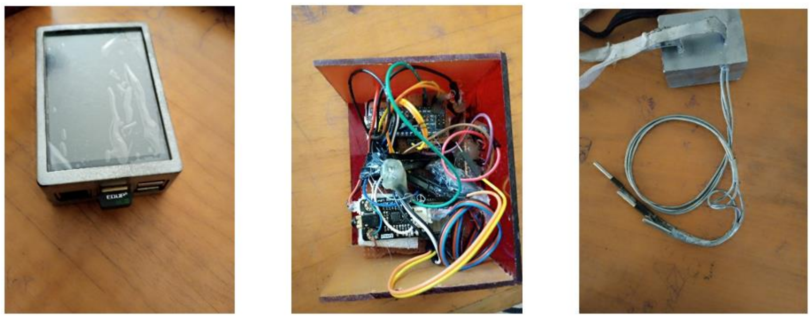
The sign-up page allows users to create an account by entering their personal and contact information, as well as creating a username and password. This page also includes a privacy policy and terms of service agreement that users must accept before creating an account. The menu page provides access to the various features and resources available within the app. It includes options such as a symptom checker, a medication reminder, and a directory of veterinarians. The search feature on this page also allows users to access camera control of the app, enabling them to take images of the skin disease and have them classified using the trained MobileNetV2 model.

The data chart page allows users to track their farm animal's health information, including weight, temperature, and other vital signs. It also includes a graph that visualizes the data over time, allowing users to easily see any trends or changes in their farm animal's health.

Overall, the mobile app for the veterinary support system provides a comprehensive range of resources and tools for farm animal owners and veterinarians to manage the health and well-being of their animals. It offers a convenient and easy-to-use platform for accessing important information and resources and helps to improve the quality of care for farm animals.

4.3 Overview of the module for the IoT System for Veterinary Support System

Figure 13 illustrates the hardware components of an Internet of Things (IoT) system designed to support veterinary healthcare. At the center of the system is a Raspberry Pi with a display running a Flask server, labeled as "a," which serves as the gateway for the system. This device is responsible for collecting data from the sensor nodes and transmitting it to the app server on Azure, where it can be accessed by veterinarians or other healthcare professionals. Connected to the gateway are two sensor nodes: an ECG sensor node labeled as "b" and a rectal temperature sensor node labeled as "c." These sensor nodes are used to collect data from the veterinary patient, such as heart rate and body temperature. This data is then transmitted to the gateway for further processing and analysis. By using these hardware components in combination with the MobileNetV2 model and VetSort mobile app, healthcare professionals can remotely monitor the health of their patients and provide timely treatment as needed. This system enables more efficient and effective healthcare delivery for veterinary patients.



(a) (b) (c)

Fig. 13 (a) IoT Gateway and Sensor Nodes for Veterinary Support System: IoT Gateway (Raspberry Pi with Display Running Flask Server), (b) ECG Sensor Node, (c) Rectal Temperature Sensor Node

5 Conclusion

In conclusion, the use of Internet of Things (IoT) and MobileNetV2 for the detection and classification of skin diseases in farm animals has the potential to be a valuable tool for improving the accuracy and efficiency of diagnosis and treatment, and for improving the health and welfare of farm animals. By integrating IoT technology with deep learning models such as MobileNetV2, we have created a system that can remotely monitor and collect data on the health and welfare of farm animals, and use this data to detect and classify skin diseases. This could be particularly useful in large-scale farming operations, where it may be difficult to manually monitor the health of all animals by deploying cameras that will be serving images to the endpoint of the model. However, it is important to note that the use of IoT and deep learning models for the detection and classification of animal skin diseases is still an area of active research, and further work is needed to develop and validate these approaches. Additionally, the use of these technologies would need to be integrated into a broader system for the diagnosis and treatment of animal skin diseases, and would need to be used in conjunction with other diagnostic tools and techniques. Overall, the potential benefits of using IoT and MobileNetV2 for the detection and classification of animal skin diseases are significant, and further research and development in this area is likely to lead to significant advances in the field.

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