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Smart Agriculture Based on IoT and Machine Learning

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Abstract — **The IoT advancements have majorly influenced in redefining the agricultural field. A reliable remote monitoring system is the need of the hour. In this paper, two objectives are addressed. Firstly, an app based solution is presented which helps in displaying the current sensor values that efficiently aid in remotely administrating the field. Secondly, an IoT based prototype system for surveillance is proposed that embeds the concept of multi-class classification technique using Machine and Deep Learning for the labels clear farm, horse, cow, wild elephant and wild boar. Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) were analysed for this purpose and the best model was chosen based on accuracy metric.**

Keywords— Agriculture, Internet of Things, Machine Learning, ARDUINO, Node MCU, Sensors, App, Support Vector Machines, Convolutional Neural Networks

I. INTRODUCTION

In the present day scenario, one of the most booming technologies is Internet of Things (IoT), which is a platform where heterogeneous sensors, actuators and protocols come under a single umbrella, thus enacting a single sophisticated system. The main aim of IoT is to work diligently upon existing data and technology and provide an adaptable and yet efficient system without letting the user realize the background heterogeneity involved in designing the system. Since IoT aims in solving the principle aspects of everyday-life, it can be induced in solving real time problems in various fields such as industries, agriculture, healthcare, etc. Agricultural field is however still plagued with inefficient monitoring and alert systems. This may lead to financial and economic loss for the farmers [1]. Thus, imbibing the very ideology of IoT, aims in solving these challenges in a cost-effective and efficient manner.

In the previous work, many variations of smart agriculture systems were developed. Some of these recent systems are tabulated in Table I [2-7]. If the feature isn't available, it's denoted by "N" or else by "Yes". Along with this, several machine learning techniques have been used to improvise the existing technologies used in farms. Disease classification at various crop parts have been achieved by implementing robust models [8-9]. Efficient Machine and Deep Learning models have been implemented for leaf disease classification [10-12]. Effective monitoring of intruders using image processing techniques is described in [13-15]. Cattle classification using various Support Vector Machines (SVM) kernels is analyzed in [16]. Other related works can be found in [17-24]. The aim of the system proposed in this paper is to incorporate all the features that are proposed in previous works and additionally to add an App based alert system for wild animal farm intrusion.

TABLE I.

VARIATIONS OF SMART AGRICULTURE SYSTEMS

Ref. No.	**[2]**	**[3]**	**[4]**	**[5]**	**[6]**	**[7]**	**Our Work**
Temp.	Y	Y	Y	Y	Y	Y	Y
Humidity	Y	Y	Y	Y	Y	Y	Y
Moisture	N	N	Y	Y	Y	Y	Y
Others	Motion	N	N	N	Water Level	Biosensor	Motion Sensor, Water Level, Raindrop Sensor, Gas Sensor, LDR , Pressure Sensor
Output	SMS	MMS	SMS	E-mail	Motor Switching	App	App
ML	N	N	N	Y	N	N	Y
Feature	Smart irrigation system animal intruders warning system proposed.	If sensor values drop below the threshold, the	The photos captured by the camera module are used to analyze the leaf type and whether it is affected by any disease.	Naive-Bayes algorithm based classification performed to check whether or not the sensor values are within the threshold range.	Automatic Irrigation System designed using cloud and zigbee implementation.	Remote monitoring of farms using an app. Biosensor is used to check the level of infection in the plants and notify the farmer.	A holistic farm monitoring and deep learning based farm intrusion system using IoT

In this paper, two objectives are proposed. One, a unified farm monitoring system is designed to aid the farmer in round the clock monitoring of his field. It also provides an automatic decision-making system which aims in almost nil intervention of the farmer.

An app, named 'GRAiN', is developed using MIT App Inventor so that the sensors can be monitored efficiently by the farmers. Secondly, an analysis using Support Vector Machines (SVM) and Convolutional Neural Networks (CNN) is performed for image classification of labelled data namely, clear farm, horse, cow, wild boar and wild elephants is done. This is to ensure that the farm and farm animals are protected from other animal intruders. A situation-oriented robust model with higher accuracy is suggested that would aid in surveillance of the farm without the intervention of the farmer.

II. METHODOLOGY

In this section, a detailed description of the proposed system is provided, along with the procedure involved in designing this system. Also, a brief description of machine learning models used in implementing multi-class image classification is presented in the latter subsection.

A. *Proposed System*

The proposed system aims to achieve two objectives as illustrated in Fig. 1. Firstly, this paper aims to propose a ubiquitous IoT solution to monitor the farm remotely by the farmers. The hardware components used in this project are tabulated in Table II.

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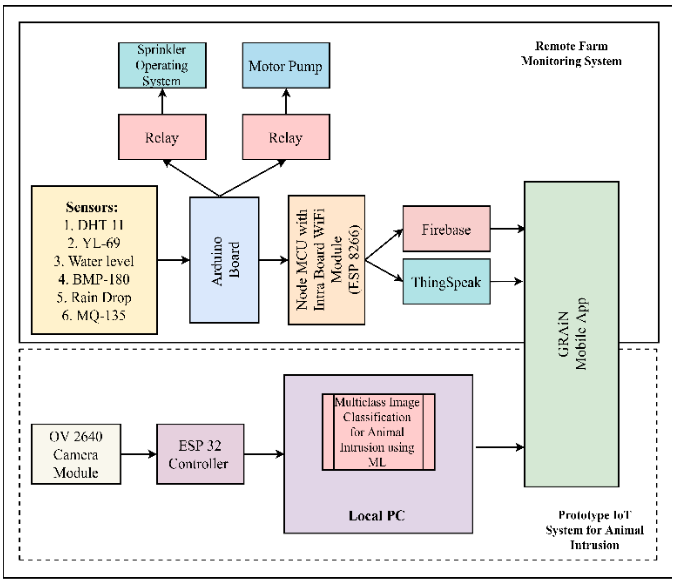

Fig. 1. Block Diagram of Proposed System.

The sensors mentioned in Fig. 1 are connected to the Arduino Mega board. At regular intervals of time, the respective measurements are made. A relay is also connected to the Arduino board, which works on the principle of electromagnetic induction. When a relay is energized, it opens or closes the contacts in an electrical circuit. A 5V, 10A 2- channel relay interface board is used in the implementation of the Sprinkler Operating System and Water Level Monitoring System where a large current is involved in operating the motor used.

A serial communication is established between Arduino Mega and Node MCU. Two cloud platforms, namely Firebase and ThingSpeak have been used to display the current sensor reading and real-time graph.

TABLE II.

HARDWARE COMPONENTS

Sensor	Operating Condition	Signal Type
Soil Moisture Sensor (YL-69)	5V	Analog
DHT 11	3.3 or 5V	Analog
Water Level Sensor	3-5V	Analog
Rain Drop Sensor Module	5V-33V	Digital
MQ-135 Gas Sensor (Smoke –Forest Fire)	5V	Analog
LDR	-	Analog
Pressure Sensor	5V	Digital

Finally, 'GRAiN', an Android app developed using MIT App Inventor This app is developed using MIT App Inventor, which provides an open source platform that allows users to drag and drop visual objects to create an application that can run on android devices. The sensor values are sent to Firebase and then the app collects the values to display the readings. This app can be used to aid the farmers with remote monitoring of the farm. The overall system can be further classified as:

a. *Parameter Monitoring System*

The sensors mentioned in Fig. 1. pass the readings to the Arduino Mega Board. As mentioned earlier, a serial communication is established between Arduino and NodeMCU and the values are sent to a real-time cloud database, i.e., Firebase. The current sensor values are

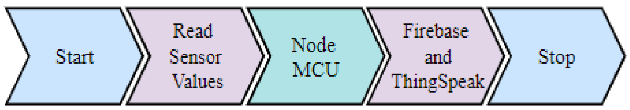

Fig. 2. Flowchart of Parameter Monitoring System

displayed on GRAiN. Simultaneously, these values are sent to ThingSpeak, which provides an open source platform to store and analyze the sensor readings. ThingSpeak graphs are also integrated with the app. The flowchart is depicted in Fig. 2.

b. *Sprinkler Operating System*

Depending on the level of moisture present in the soil obtained from soil moisture sensor, the system is programmed whether or not to activate the relay circuit. Whenever the soil moisture level is lower than the threshold value, a signal is send from Arduino to activate a relay. It is assumed that this relay circuit is connected to a system which further activates the sprinkler system. The flowchart is given in Fig. 3.

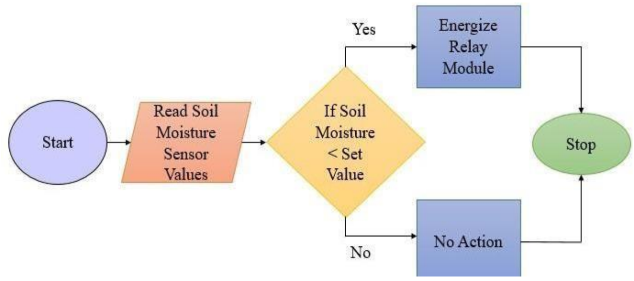

Fig. 3. Flowchart of Sprinkler Monitoring System

c. Sprinkler Operating System

It also works on the similar principle of Sprinkler Operating System. The only difference is that the decision making is based on the level of water, which is detected by the water level sensor and based on the reading, the relay is activated, which further is assumed to be connected to a motor that pumps water. The block diagram and flowchart are presented in Fig. 4-5.

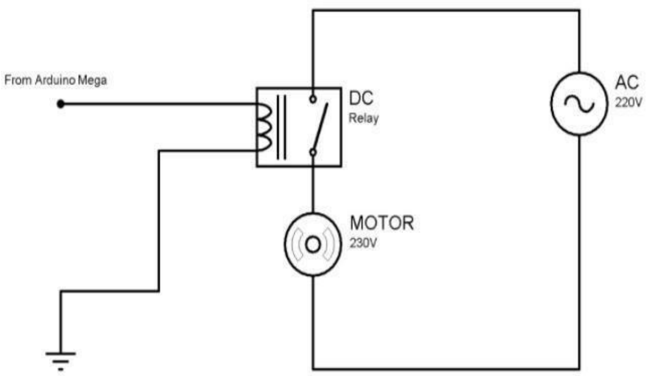

Fig. 4. Circuit Diagram for Water Pumping System

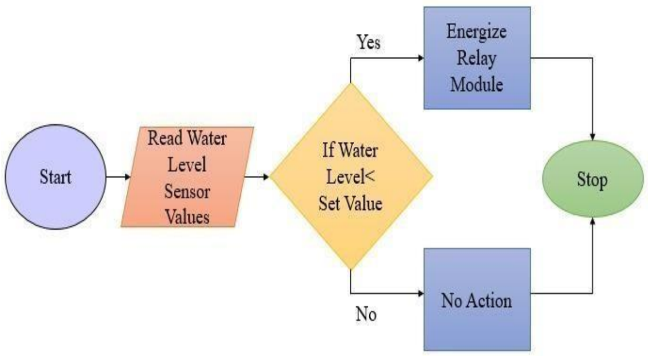

Fig. 5. Flowchart of Water Level Monitoring System

The second objective of the paper is to propose a prototype IoT system for animal intrusion. The proposed system is interfaced with a camera module, which has a camera and a 32 bit microcontroller. This camera module is featured with an OV2640 camera, several GPIOs to connect peripherals, and micro-SD card slot. The live streaming, captured by the video of the camera can be played on a Local PC. It is assumed that in the Local PC, the frames of the video stream are assumed to be extracted at regular intervals and stored as images. These images are fed to the best machine or deep learning model obtained post analysis. The model identifies whether a farm or wild animal is near the premises of the farm and accordingly the app notifies the farmer in prior, so that he can take necessary measures to protect the farm from being attacked.

B. Machine learning Models

As mentioned in the previous subsection, the proposed system involves a situation based multi-class classification of the animals. 200 colour images of the size (256 x 256) are conglomerated under the labels namely, clear farm, horse, cow, wild boar and wild elephants. The analysis is done with respect to various practical situations. These are tabulated in Table III. The models chosen for analysis are described below.

TABLE III.

SCENARIO DESCRIPTION FOR ANIMAL CLASSIFICATION

No.	**Scenario**	**Classificat ion**	**Harmless Situation**	**Intruder Animal**
1.	**Clear farm, Farm Animal, Wild Animal**	3	1. Clear Farm 2. Cow and Horse	3. Wild Boar and Wild Elephant
2.	**Only Elephant and Cow**	3	1. Clear Farm 2. Cow	3. Wild Elephant
3.	**Only Elephant and Horse**	3	1. Clear Farm 2. Horse	3. Wild Elephant
4.	**Only Boar and Cow**	3	1. Clear Farm 2. Cow	3. Wild Boar
5.	**Only Boar and Horse**	3	1. Clear Farm 2. Horse	3. Wild Boar
6.	**Only Elephant**	4	1. Clear Farm 2. Cow 3. Horse	4. Wild Elephant
7.	**Only Boar**	4	1. Clear Farm 2. Cow 3. Horse	4. Wild Elephant
8.	**All**	5	1.Clear Farm 2.Cow 3.Horse	4. Wild Boar 5. Wild Elepha nt

Support Vector Machines (SVM)

Support Vector Machine (SVM) is a supervised classification machine learning model. It is a non-parametric algorithm that obtains a N-dimensional hyperplane that distinctly classifies the labelled images. SVM has a kernel function that takes data as input and transforms it into the required format. The Kernel Function converts the training data from a non-linear decision surface to a linear equation in a higher number of dimension spaces. Here, the default kernel function, i.e., Radial Basis Function is used as RBF kernel works well in practice and it is relatively easy to tune.

Convolutional Neural Networks (CNN)

The key benefit of CNN over its predecessors is how it identifies essential features without a need for human intervention. A class of deep learning techniques that incorporates the principle of convolution operation, CNN consists of an input and an output layer, and one or many hidden layers that is constructed with a series of convolutional layers. The neural network being a "black box" is architectured to "learn" the filters that were pre- designed in the conventional algorithms. The attributes of the CNN network are defined by convolutional kernels, number of input channels and output channels and depth of the convolution filter.

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 85, 85, 128)	3584
max_pooling2d (MaxPooling2D)	(None, 42, 42, 128)	0
dropout (Dropout)	(None, 42, 42, 128)	0
activation (Activation)	(None, 42, 42, 128)	0
conv2d_1 (Conv2D)	(None, 14, 14, 128)	147584
max_pooling2d_1 (MaxPooling2	(None, 7, 7, 128)	0
dropout_1 (Dropout)	(None, 7, 7, 128)	0
activation_1 (Activation)	(None, 7, 7, 128)	0
conv2d_2 (Conv2D)	(None, 2, 2, 128)	147584
max_pooling2d_2 (MaxPooling2	(None, 1, 1, 128)	0
dropout_2 (Dropout)	(None, 1, 1, 128)	0
activation_2 (Activation)	(None, 1, 1, 128)	0
feature_dense (Flatten)	(None, 128)	0
dropout_3 (Dropout)	(None, 128)	0
dense (Dense)	(None, 4)	516

Fig. 6. Algorithm for CNN model creation

A sequential CNN model is initialized and the model is trained using a custom dataset consists of total 2000 images. The architecture of the CNN mo9del is given in Fig. 6. The model is very light weight having 299,268 parameters.. The above algorithm runs for 600 epochs until good accuracy is achieved with minimum loss. To get a better accuracy and to avoid over-fitting, dropout is used to slow the training process.

III. Implementation and Results

A. *Hardware*

The sensors are all interfaced with Arduino Mega Board. Soil moisture,DHT11, Gas Sensor, Pressure Sensor and water level sensors produce analog outputs and hence were connected to the analog pins of Arduino Board, whereas, DHT 11 and Rain Drop Sensor Module are interfaced to digital pins. At regular intervals of time, the sensor readings are recorded and an Inter Serial Communication is established between Arduino and NodeMCU. With the intra-board WiFi Module, the sensor values are transmitted to Firebase and ThingSpeak. A separate camera module is connected for providing surveillance to the farm. The ESP32, typically acts as a web server that serves a web page that captures binary image data to display it on an HTML5 canvas.

B. *App Design*

GRAiN, developed by MIT App Inventor, is used to aid the farmers with remote monitoring of the farm. The drag and drop features provided by the IDE, helps the users to create apps on the go. One of the recent features allows the app-enthusiasts to connect with Google's Firebase. The sample block connection is shown in Fig. 7 and the final design of the app as seen in the Android phone is depicted in Fig. 8.

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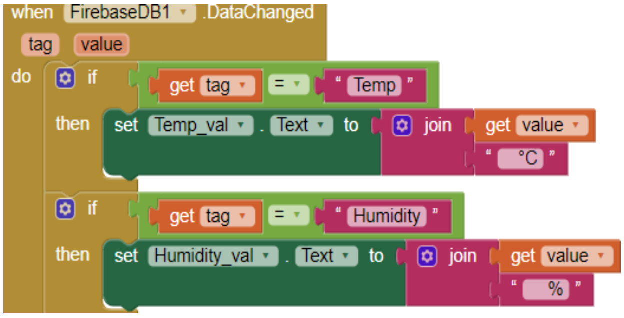

Fig. 7. Block Connection of Firebase to MIT App Inventor

Fig. 8. GRAiN App Final Design Preview

The graphs are plotted with updating real-time values in the cloud platform provided by ThingSpeak. When each of these labels is pressed, the graph can be viewed. It is to be noted that, for each sensor reading a separate field was created in ThingSpeak. An example of the humidity graph varying with respect to time is shown in Fig. 9.

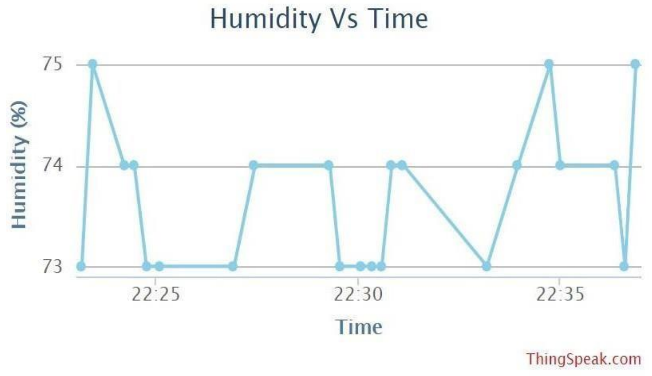

Fig. 9. ThingSpeak Graph for Humidity

The model was compiled for categorical cross entropy loss and 'adam' optimizer was used to estimate the accuracy metric. The CNN model trained for 600 epochs. Table IV presents the model performance for each of the scenarios.

In all the cases CNN showed better performance than SVM. When the models were trained with generalized label, like in Scenario-1, both CNN and SVM showed a poor performance. This is because, the models were trained to learn many features, under the same label. For example, under the label of 'Farm Animal', the algorithms were put in a situation to learn the discrete features of Cow and Horse. When the labels were explicitly specified, the models classified the animals better. This can be observed in cases labelled 2-7.

Another observation made was that, specific scenarios showed better accuracy, proving the performance of training the models only with relevant data and excluding the redundant information. For example, in Scenario 4, the models were trained for a farm situation where only 'Clear Farm','Cow' and 'Wild Boar' are involved. It comes with an assumption that 'Horse' and 'Wild Elephant' are absent and hence the models were not trained with these data. Such specific training of the models have achieved higher accuracy. This can be observed in 2-5. When the number of multi-classes increased, the robustness of the models reduced, impacting the evaluation metric as observed in 6-8. This is because, the models are to be trained to learn many features specified.

The accuracy plot can be observed in Fig. 10. The average performance of SVM in all cases is 74.46% and CNN is 89.13%, proving that CNN performed 16.46% better than SVM. Also, the average of all the CNN models accuracy after 600th epoch is 86.88% which just has 2.45% difference, proving the the CNN model constructed to perform multi-class classification is highly stable. The model that performed the best for this dataset is the one with only boar and horse, in both SVM and CNN with an accuracy of 83.3% and 92.7% of mean accuracy, respectively.

TABLE IV
SCENERIO DESCRIPTION FOR ANIMAL CLASSIFICATION

No.	SVM	CNN Accuracy After 600^{th} Epoch	CNN Mean Accuracy
1.	0.765	0.867	0.8512
2.	0.800	0.938	0.909
3.	0.767	0.968	0.920
4.	0.825	0.951	0.910
5.	0.833	0.961	0.927
6.	0.731	0.8118	0.8372
7.	0.665	0.892	0.850
8.	0.571	0.7416	0.7460

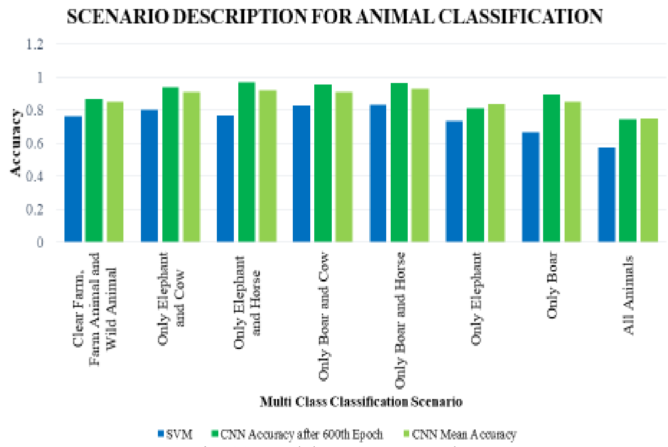

Fig. 10. Model Accuracy Graph

IV. CONCLUSIONS AND FUTURE WORK

The implementation of Internet of Things in the farm-monitoring system ensures an easy and efficient way of supervising the farm conditions and taking necessary actions, which thereby ensures proper utilization of natural and other resources. This work constituted on successfully achieving 2 objectives, namely an app based farm monitoring system and a multi-class animal classification model. In the latter objective, it was observed that CNN model showed a promising performance for labelled image classification compared to the SVM model. Here, the actuators to run for sprinkler system and water monitoring systems are assumed to be connected to the implemented system which can realized in hardware. Also, the extraction of camera inputs as frame by frame to the SVM and CNN models isn't covered in this paper.

This work can be further extended by including a much more interactive app and alert systems. Also, more sensors and actuators can be included in this scalable system to aid the farmer. Furthermore, prediction models can be developed to perform forecasting and perform model optimization on CNN to gain more accuracy. The prediction systems including the assumed inputs can be implemented on an embedded systems to obtain a holistic smart farming model.

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