Intelligent disease detection and treatment in crops using UAV

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***Abstract*— Occurrence of diseases on rice plants degrades the quality and decrease in quantity of yield. Therefore, earlier detection of plant disease will help to prevent the rice from severe infection and avoiding crop loss. Recently, drones have been used in agriculture monitoring together with the camera and GPS sensor. It is an alternative tool to obtain data quickly and autonomously in a large-scale area. For better rice productivity, this project presents the implementation system of drone-based on the Internet of Things(ioT) architecture using real-time information including data acquisition and data analysis using image processing techniques to perform rice disease detection, it's subsequent classification and appropriate treatment. The system is capable of displaying the analytic results including the position of infected rice plants mapping them on rice fields by using a GPS sensor to define the position in real-time along-with taking necessary steps to handle them. This system is proposed as a preliminary to support system for early and real-time disease detection with the implementation of ioT architecture.**

Keywords*— *ioT; Deep Learning; Image Processing; UAV;

I. Introduction

In this project, we will focus on diseases presenting on leaves and caused by a pathogen (fungi and bacteria). The occurrence of rice diseases could cause a serious decrease in rice productivity. Once the diseases appear, it should be detected and identified in order to avoid loss by caring for rice crops as soon as possible before they become more severe. Therefore, implementing ioT architecture in agriculture with drones together with image processing is another challenge but it will provide advantageous to the agriculture system. The advantages of using a drone instead of human labour are that it can reduce time consumption for the field survey, do tasks in a larger area, is capable of processing all tasks, notifies the user promptly and is capable of protecting their crops from the disease which results in yielding more productivity. The crop diseases can be controlled by identifying the diseases as soon as it develops on crops.

II. Integrity

A. Background Study

The authors in [1] present the characteristics and requirements of UAV networks for envisioned civil applications over the period 2000–2015 from a communications and networking viewpoint. They survey the quality of service requirements, network-relevant mission parameters, data requirements, and the minimum data to be transmitted over the network for civil applications. They also discuss general networking related requirements, such as connectivity, adaptability, safety, privacy, security, and scalability.

B. Related Work

The identification of the crop species is the basic requirement before we identify the class of disease. Abdul Kadir in his research work has used colour features like mean, standard deviation, skewness and kurtosis are made on the pixel values of the leaves. He has consolidated features coming through grey level co-occurrence matrix (GLCM) functions which identifies the texture of an image. It generates a GLCM that produce statistical measures by calculating how frequently pairs of pixels with specific values and in a specified spatial relation occur in an image [2]. In paper [3], neural network is used to detect the disease. If leaf is infected, further processing is done to identify the disease. Genetic algorithm is used along with SVM to optimize loss and identify the type of disease. This paper states method for optimization of loss function using genetic algorithm, which is similar to theory of natural selection w here only strong parameters survive. In paper [4], semi-supervise learning is used in the form of Generative Adversarial Networks to classify images. In such type of learning discriminator is transformed into a multi-class classifier and generator is used only for training of discriminator. In paper [5], transfer learning is used for content-based image recommendation and Inception-V3 model is used for building of neural models.

Monica Jhuria et al uses image processing for detection of disease and the fruit grading in [6]. They have used artificial neural network for detection of disease. They have created two separate databases, one for the training of already stored disease images and other for the implementation of the query images. Back propagation is used for the weight adjustment of training databases. They consider three feature vectors, namely, colour, textures and morphology [6]. They have found that the morphological feature gives better result than the other two features.

C. Novelty

The main objective of this project is to find the diseases that threaten the cultivation and devise ways for their mitigation. Multiple research works have been carried out in recognising diseases in plants and thereby, have been referred from (citations included). Most of the work is in paper and hence, practical implementation using UAVs has been demonstrated only by a few research-based institutions. Additionally, attaching a medicine dispenser for treating the diseased plants on immediate basis (upon detection) hasn't been in practice anywhere and is entirely a new concept. Hence, this project is novel with a large margin from its forerunners.

III. TECHNICAL HIGHLIGHTS

A. *Implementation of IoT Architecture*

The drone is powered by a 12V LiPo battery and the required thrust is provided by 4 BLDC (1000kV) motors, which offers a payload of 978g. The commands for manoeuvring are received by a PixHawk controller mounted on the chassis. A FPV 600TVL Camera captures the live feed and transmits it to the base via a TS832 (transmitter) and RC832 (Receiver) couple. A power distribution board distributed voltage across the motors, camera and the receiver with a constant current constraint.

The authors of [7] provide a comprehensive survey on UAVs, highlighting their potential use in the delivery of Internet of Things (ioT) services from the sky. They describe their envisioned UAV-based architecture and present the relevant key challenges and requirements.

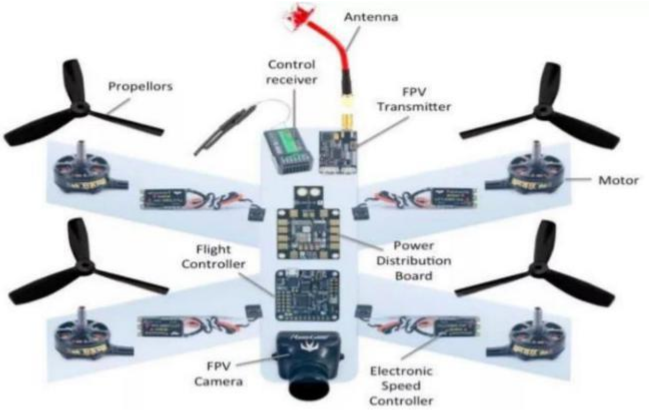

Figure 1: UAV Assembly

B. *Implementation of Image Processing Techniques*

- Image acquisition – The aerial feed from FPV camera is transmitted to the base station which then forwards it to the pre-processing stage. This image is in RGB form. Colour transformation structure for the RGB leaf image is created, and then, a device-independent colour space transformation for the colour transformation structure is applied
- Image Pre-processing – The image is passed through an array of filters to prepare it for feature extraction. To remove noise in image or other object removal, different pre-processing techniques are considered. Image clipping i.e. cropping of the leaf image to get the interested image region. Image smoothing is done using the smoothing filter. Image enhancement is carried out for increasing the contrast.
- Image Segmentation – The processed image is then sampled at a sampling frequency by using various methods like Otsu' method, k-means clustering, converting RGB image into HIS model etc. that prepares it for the feature extraction phase.
- Feature Extraction – The image is now consolidated with a fixed instance of features generated for the expected images and stored in a xml file which extracts the desired features from the image and makes detection faster as well as computationally efficient.
- Classification – The extracted features are then fed into a pre-trained deep learning model that does its part of detection and recognition (classification) of the diseased areas.

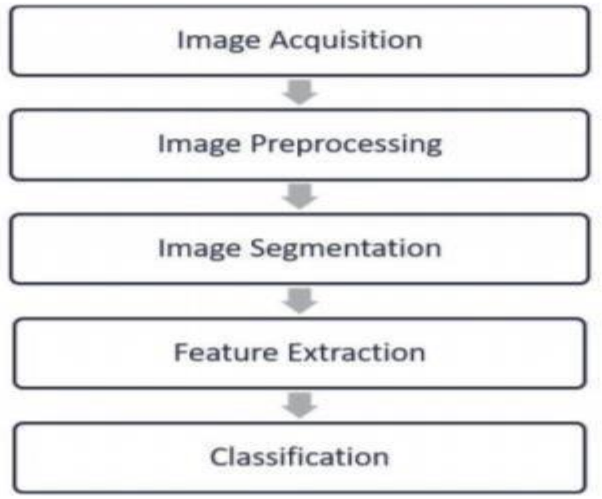

Figure 2: Image Processing Steps

C. *Map Generation Technique*

The camera feed transmitted is displayed on the interface and makes controlling the drone convenient. The GPS coordinates of the areas with diseased crops are returned to the base station and fed into the interface wherein, a map comprising of the spots is generated for better visualisation of results.

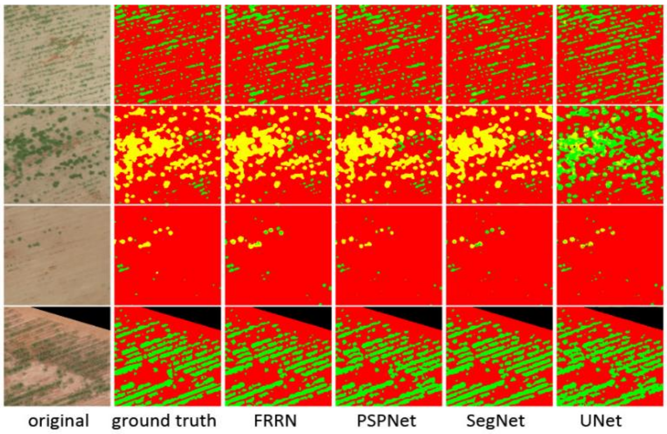

Figure 3: Map generation by different models

D. *Deep Learning Approach*

Classification of the disease is performed in two steps where the first step is to detect the type of crop and second step is to detect the type of disease. To perform these task deep convolutional neural networks is used. Transfer learning is used to build the deep learning model and is trained using the ImageNet dataset. Transfer learning is a machine learning technique in which a model is trained on one task is repurposed on another related task. It is a technique in which pre-trained neural networks are used to build the neural network for similar kind of task to implant rapid and sustainable progress for solving the problem.

E. Datasets

Plantvilla which is an open source dataset is used which contains 54,306 images of crop leaves classified in 38 different classes. The dataset covers 13 type crop species and 26 types of diseases. Each class has pair of fields containing the name of crop and the name of disease. All these images are segmented and resized to 224 x 224 size and are converted into grayscale images before further processing.

F. Pre-processing of image

The images present in the dataset have varying background and non-uniform lighting which affects accuracy of the application. The pre-processing of image is essential for removing noise and segmentation of the image which helps in improving the accuracy of CNN model. Hence, to handle the 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA) varying background problem, segmentation is performed that extracts only relevant part of the image. So, after performing the segmentation all the leaf images with black background are obtained. Further, to handle the non-uniform lighting conditions segmented images are converted to grey scale images and are passed on for further processing.

G. Crop disease detection and classification

Several research organizations build such kind of models which take weeks to train on latest high-end hardware. These are released under a permissive license for reuse that are directly incorporated to build new model for solving similar type of problems. These pre-trained models can be fine-tuned by using new dataset, if its nature is similar to the dataset on which network is trained. In such type of cases only last layer of network is trained, then tuned network can be directly used to solve problem. If the size of dataset is large enough then the pre-trained model can be retrained using new data and, in such case, the neural network is initialized with weights of the pre trained model.

Transfer learning is used to build deep learning model using MobileNet and InceptionV3 pre-trained models. These models are fine-tuned by using image dataset of 5 different types of crops with 5277 images. These models are initialized with the weights of the pre-trained model. Dataset is pre-processed and divided into 80%-20% training and testing data. Label encoding is used for conversion of output to categorical type. Image data generator is used to introduce variation in the input images. A dense layer is appended with the softmax activation function to extract the result from model. Adam optimizer is used with the categorical cross entropy as loss function. These pre-trained models are then retrained for 10 epochs with batch size of 8 by using new training dataset to create required model. Dropout of 1e-3 is added to overcome the problem of overfitting. Generated model is tested using testing dataset to find out validation accuracy. Performance of both the models is measured on the basis of training accuracy, training loss and validation accuracy, validation loss per epoch.

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1 Conv / s1	$3 \times 3 \times 512$ dw $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Figure 4: Architecture of MobileNet

A dedicated deep convolutional neural network is used to detect disease related to individual crop which incorporates similar methodology of plant detection. There are multiple models generated for disease detection each corresponding to a particular type of crop. The type of plant is detected using previously mentioned model which determines to which disease detection model the image should be passed on for detection of the type of disease. The models build for identification of disease are evaluated using testing dataset on the basis of training accuracy, training loss and validation accuracy, validation loss per epoch.

IV. PROPOSED SYSTEM WALKTHROUGH

A. Capturing of Images

A camera, interfaced with the main controller on the quadcopter, the Ardupilot, which is mounted on a UAV and is used to keep our area under constant surveillance. The images that are taken by this camera is transmitted by ardupilot to the main system, where the images are processed by frame by the OpenCV using python programming language. We utilize Ardupilot Mega board, which is an Arduino Mega based open source platform, which is generally used as a flight controller for motor control operation of Quadcopter. The major reasons for choosing this controller is due to its simplicity in control and the two-way telemetry and in-flight direction utilizing the great MAVLink convention. It gives decision of free Ground Stations, which incorporates unique tasks, such as video and camera controls, on-board video display, voice union, and full datalogging with replay.

Figure 5: Ardupilot Mega

An ESP8266 is interfaced with the Ardupilot. The nodeMCU and serial protocol MAVlinks helps in transmission of data from the controller using wifi. We use Logitech HD PRO Webcam C920 camera for computer vision which is interfaced with Ardupilot. The camera has a 15 Megapixel camera with focus type of 20 autostep. The full HD glass lens with precisely tuned autofocus and full HD 1080p video with automatic noise reduction. Automatic low-light correction, video and photo capture, Face tracking, Motion detection are present. The camera captures the images for image processing. The Logitech camera and Ardupilot interfaced system is set on a UAV, which covers the entire land area to obtain images.

A Portable Power Bank is used to provide power to the Ardupilot system. The location of the image detected is provided to the farmer using GPS This module named Neo 6M-0-00-1 U-Blox operating at 5V DC. Global Positioning System is used for tracking the location of each Device placed in various parts.

B. Software Operation

The operation of software mainly involves processing of images obtained from the quadcopter to detect pests, disease and weed in the area. For this, the area is monitored and images are captured using camera. The captured images are sent to the central PC or laptop for image processing. The image processing involves CNNs which employs use of both Support Vector Machine and K mean clustering. The Support Vector Machine and K mean clustering are employed image processing. We use K mean cluster for its efficiency in segmentation of images and we use Support Vector machine (SVM) because SVM provides better results in extraction of colour and texture. Training datasets are selected based on the knowledge of the user.

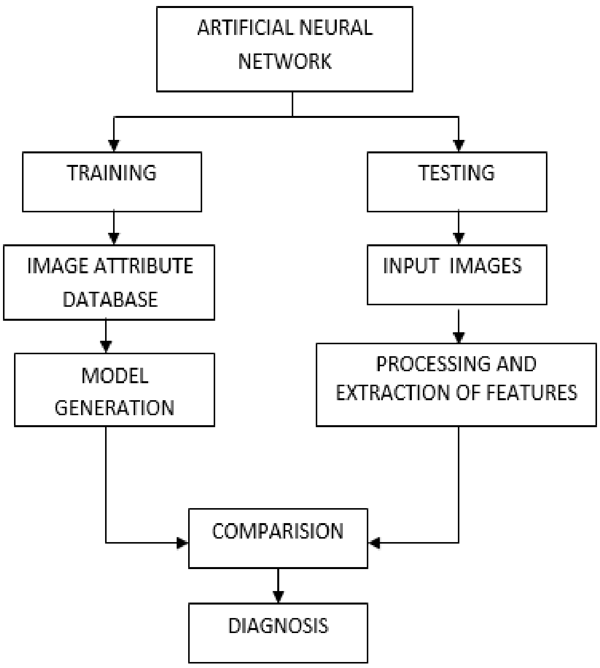

Figure 6: Algorithm

For disease detection, the images are also compared with the default modelled datasets provided to the system in SVM comparison.

The comparison is done based on threshold, using SVM. The similar technique is used to detect the damages caused to the crops by the pests. The algorithm for generation of model is given in figure 6. However, for detection of physical pests, the successive images are compared using the matrices. By comparing the colour and motion of pest through the images, we detect the presence of pests.

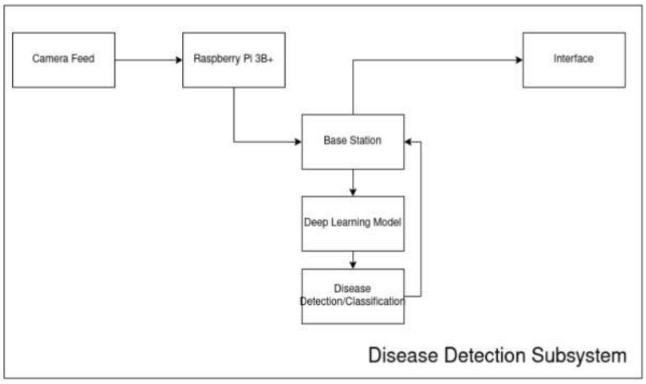

Figure 7: Block Diagram for Disease Detection Subsystem

C. Hardware Requirements

- Quadcopter Frame
- BLDC Motors
- PixHawk Flight Controller
- FPV 600TVL Camera
- Transmitter (TS832) and Receiver (RC832)
- Remote Controller Module
- Bull Nose Propeller
- GPS module (Ublox neo m8n)
- Medicine Dispersal Mechanism

D. Software Requirements

- ArduPilot
- Mission Planner
- trueHWIL
- Python (OpenCV, Tensorflow, pySerial, WiringPi)

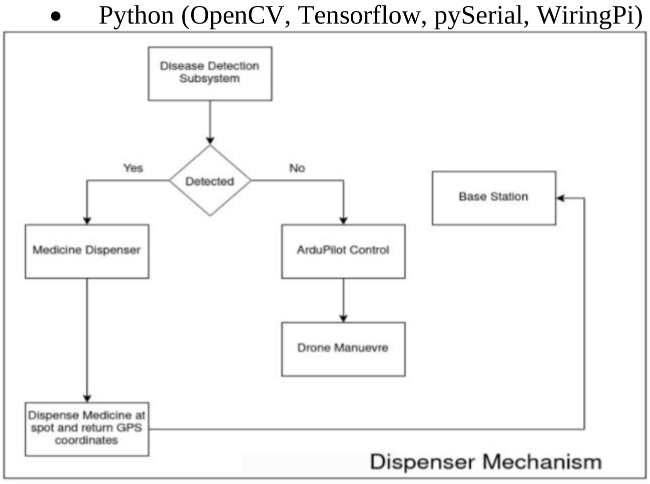

Figure 8: Block Diagram for Dispenser Mechanism

IV. OUTCOMES

After the experimentation on trained model it is found that model trained using segmented images perform better than model trained using colour and grey-scale images. In case of experimentation for detection of crop type, as per Fig 4-7 both MobileNet and InceptionV3 models perform well with 99.62% and 99.74% accuracy respectively. Significant growth in accuracy is observed in initial stages which get converged later on. Exponential drop in loss function signifies faster learning in the initial stage. It is observed that InceptionV3 model performs better than MobileNet in the task of crop detection.

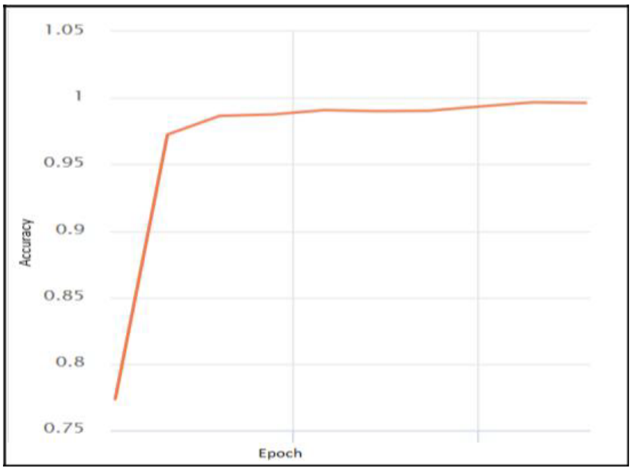

Fig 9. Accuracy Vs Epoch for crop detection for MobileNet

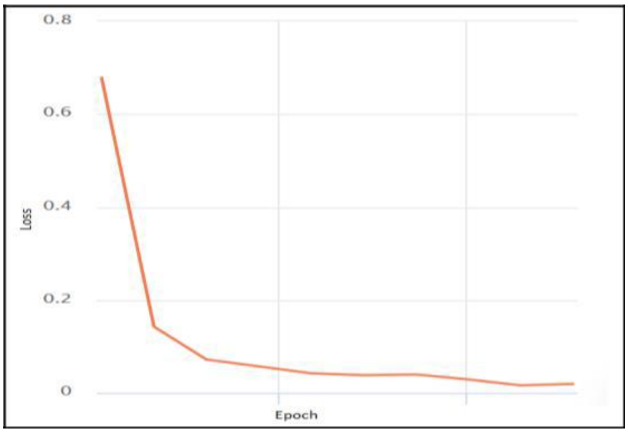

Fig 10. Loss Vs Epoch for crop detection for MobileNet

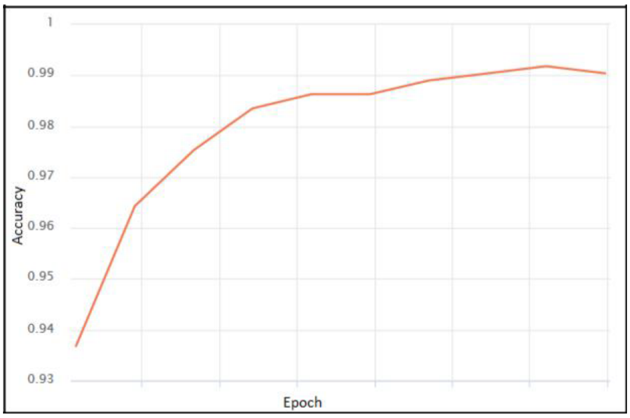

Fig 11. Loss Vs Epoch for disease detection for MobileNet

In similar way for crop disease detection both MobileNet and InceptionV3 models shows steady growth with 99.04% and 99.45% accuracy respectively. Slight decrement can be observed in the accuracy from 6th epoch to 7th epoch in case of InceptionV3 model. Value of loss function at the end of 10th epoch supports the better performance of InceptionV3 in the task of disease detection.

Specifically, the innovation of Faster R-CNN lies in replacing the previous slow selective search algorithm with region proposal network (RPN), which runs much faster than before. Faster R-CNN methods include four steps: region proposal generation, feature extraction, classification, and location optimization. For inputting images of any size, the RPN uses CNN to directly generate a batch of region proposals and then fine-tunes candidate frames and classifications. Faster R-CNN output will predict every anchor being object or background. It resulted in a 10x increase in inference speed and better accuracy.

R-FCN is a region-based fully convolutional network which proposes position-sensitive score maps to avoid too much computation. This model increases the speed by sharing calculation on the entire image. And the convolution layer is added to generate the position-sensitive score maps. R-FCN can solve the contradiction between the image classification translation-invariance and the object detection translation-variance. Some studies have shown that R-FCN can achieve comparable accuracy to Faster R-CNN with shorter running times [16, 40, 41], which means it achieves a good balance between speed and accuracy.

V. CONCLUSION

The use of UAVs has become ubiquitous in many civil applications. From rush hour delivery services to scanning inaccessible areas, UAVs are proving to be critical in situations where humans are unable to reach or cannot perform dangerous/risky tasks in a timely and efficient manner. In this survey, we review UAV civil applications and their challenges. We also discuss current research trends and provide future insights for potential UAV uses.

In SAR operations, UAVs can provide timely disaster warnings and assist in speeding up rescue and recovery operations. They can also carry medical supplies to areas that are classified as inaccessible. Moreover, they can quickly provide coverage of a large area without ever risking the security or safety of the personnel involved. Using UAVs in SAR operations reduces costs and human lives.

In remote sensing, UAVs equipped with sensors can be used as an aerial sensor network for environmental monitoring and disaster management. They can provide numerous datasets to support research teams, serving a broad range of applications such as drought monitoring, water quality monitoring, tree species, disease detection, etc. In risk management, insurance companies can utilize UAVs to generate NDVI maps in order to have an overview of the hail damage to crops, for instance.

Civil infrastructure is expected to dominate the addressable market value of UAV that is forecast to reach $45 Billion in the next few years.

In construction and infrastructure inspection applications, UAVs can be used to monitor real-time construction project sites. They can also be utilized in power line and gas pipeline inspections. Using UAVs in civil infrastructure applications can reduce work-injuries, high inspection costs and time involved with conventional inspection methods.

In agriculture, UAVs can be efficiently used in irrigation scheduling, plant disease detection, soil texture mapping, residue cover and tillage mapping, field tile mapping, crop maturity mapping and crop yield mapping. The next generation of UAV sensors can provide on-board image processing and in-field analytic capabilities, which can give farmers instant insights in the field, without the need for cellular connectivity and cloud connection.

With the rapid demise of snail mail and the massive growth of e-Commerce, postal companies have been forced to find new methods to expand beyond their traditional mail delivery business models. Different postal companies have undertaken various UAV trials to test the feasibility and profitability of UAV delivery services. To make UAV delivery practical, more research is required on UAVs design.

UAVs design should cover creating aerial vehicles that can be used in a wide range of conditions and whose capability rivals that of commercial airliners. UAVs have been considered as a novel traffic monitoring technology to collect information about real-time road traffic conditions. Compared to the traditional monitoring devices, UAVs are cost-effective and can monitor large continuous road segments or focus on a specific road segment. However, UAVs have slower speeds compared to vehicles driving on highways. A possible solution might entail changing the regulations to allow UAVs to fly at higher altitudes. Such regulations would allow UAVs to benefit from high views to compensate the limitation in their speed.

An extension of this work will include the classification of images that are not captured in a controlled environment and images that have multiple orientation. Also, the number of classes of crops and its diseases can be further increased. This methodology can be integrated with smart phone applications that would provide user friendly GUI and simplicity for its usage.

The image processing system can be made more efficient by using more efficient neural networks to increase accuracy over time by using algorithms that updating the model over period of time. Efficient cameras can be used for effective detection of pests, diseases and weeds. Unlike our case where image processing is done on a separate system such as PC, suitable processors can be used, that directly provide processed data from the drone.

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