IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received May 26, 2020, accepted June 8, 2020, date of publication June 16, 2020, date of current version June 29, 2020.

Digital Object Identifier 10.1109/ACCESS.2020.3002948

A Multi-Modal Approach for Crop Health Mapping Using Low Altitude Remote Sensing, Internet of Things (IoT) and Machine Learning

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This work was supported in part by the Higher Education Commission (HEC), National Research Programme for Universities (NRPU) Program, Pakistan, and in part by the Global Challenge Research Fund (GCRF), U.K.

ABSTRACT The agriculture sector holds paramount importance in Pakistan due to the intrinsic agrarian nature of the economy. Pakistan has its GDP based on agriculture, however it relies on manual monitoring of crops, which is a labour intensive and ineffective method. In contrast to this, several cutting edge technology-based solutions are being employed in the developed countries to enhance the crop yield with the optimal use of resources. To this end, we have proposed an integrated approach for monitoring crop health using IoT, machine learning and drone technology. The integration of these sensing modalities generate heterogeneous data which not only varies in nature (i.e. observed parameter) but also has different temporal fidelity. The spatial resolution of these methods is also different, hence, the optimal integration of these sensing modalities and their implementation in practice are addressed in the proposed system. In our proposed solution, the IoT sensors provide the real-time status of environmental parameters impacting the crop, and the drone platform provide the multispectral data used for generating Vegetation Indices (VIs) such as Normalized Difference vegetation Index (NDVI) for analyzing the crop health. The NDVI provides information about the crop based on the chlorophyll content, which offers limited information regarding the crop health. In order to obtain a rich and detailed knowledge about crop health, the variable length time series data of IoT sensors and multispectral images were converted to a fixed-sized representation to generate crop health maps. A number of machine and deep learning algorithms were applied on the collected data wherein deep neural network with two hidden layers was found to be the most optimal model among all the selected models, providing an accuracy of (98.4%). Further, the health maps were validated through ground surveys and by agriculture experts due to the absence of reference data. The proposed research is basically an indigenous, technology based agriculture solution capable of providing important insights into the crop health by extracting complementary features from multi-modal data set, and minimizing the crop ground survey effort, particularly useful when the agriculture land is large in size.

INDEX TERMS Internet of Things (IoT), precision agriculture, NDVI, crop health.

I. INTRODUCTION

Pakistan is an agricultural country owing to its natural resources including fertile arable land, favorable climate conditions and the largest irrigation system in the world [1]. The agriculture sector accounts for 18.5% of Pakistan GDP [2] and has a significant impact on the economy of the country. Despite of all suitable conditions for crops cultivation, Pakistan is still unable to produce surplus yield for national and international market needs. Every year, Pakistan

The associate editor coordinating the review of this manuscript and approving it for publication was Peng-Yong Kong.

faces a huge loss in the agriculture sector due to several factors such as extreme climatic variations, lack of technology adoption, improper use of major resources like water, fertilizer, and pesticides [3]. The inappropriate utilization of these resources leads to loss of organic content & nutrients in the crop and a significant reduction in its yield. In order to address these problems, technology-based solutions should be employed to overcome the manual farming practices which are inherently time consuming and laborious.

In Pakistan, major crops wheat, rice, maize, sugarcane and cotton are planted on 8.74, 2.80, 1.30, 1.30 and 2.47 million per ha in 2018 to 2019. Among these, wheat is the staple crop of the country and typically sown from October to December and harvested from March to May [4]. The wheat plant undergoes several development stages such as seeding, tillering, booting, heading and ripening. In each stage, the wheat plant has specific requirements of water, temperature, solar radiations and nutrients / fertilizer for optimal growth. These requirements are directly correlated with climate change, for instance, the frequency of rainfall and temperature variations. For the ideal development of the wheat plant, the primary resources should be applied in a controlled fashion in a site-specific manner as the deficiency of any resource can adversely affect the crop growth where as, the excessive use of these resources can damage the crop [5]. To precisely estimate the resource requirements, Precision Agriculture (PA) is widely practiced across the world and it basically enhances the food production with optimal use of resources [6].

As of today, the smart agriculture systems based on IoT are rapidly gaining popularity as they provide real time status of the environmental variables pertaining to the crop using low cost sensors [7]. Such systems not only advance the PA practices but also play a key role in making the crop monitoring system more efficient and effective. On the other hand, the IoT based systems are generally suitable for small to medium scale farming due to their sensitivity to the high maintenance & deployment cost and power constraints. In contrast to IoT, remote sensing is widely used for large scale farming which is based on a reflective analysis of satellite images [8]. Conventionally, satellite images have been used as the key source of information for analyzing crop status in precision agriculture. But, obtaining most recent aerial/satellite imagery is very expensive, and data processing is also intensive and complicated. In addition to this, the images obtained from satellites are of low resolution and are only suitable for large scale studies. This limit their applicability in studies based on precision agriculture. On the other hand, the satellites (such as Quick Bird, ASTER) providing higher resolution images have long revisit time which makes them unsuitable for applications (such as pest monitoring, nutrient stress monitoring etc.) that require images on frequent basis [9]. To overcome these limitations, low altitude platforms such as drone with on-board imaging sensors are used, where these platforms provide high-resolution images and flexible data acquisition [6].

Typically, the multispectral data collected using drone is used to compute the VIs of the crop for determining its health status. Generally, NDVI is used as a strong indicator of crop health. However, if the crop health conditions are only determined from the NDVI values, then the inferred crop health status would be misleading due to the varying level of chlorophyll content at different stages of the crop. Every development stage of crop has some predefined range of NDVI values, which can help to assess the health of the crop. The low NDVI value does not always refer to the stressed or unhealthy crop, we have to integrate the temporal information of the crop development stage as well to determine the crop health status.

In view of the above, we have proposed a multi modal data driven approach for agricultural monitoring based on IoT, drone based remote sensing and machine learning. The proposed work is based on testing the hypothesis that *the integration of multi modal data can enhance the representation of crop health information as compared to the crop health status depicted only by NDVI.* For this purpose, the collected data from IoT nodes and drone were analyzed at different growth stages of the crop and its health maps were generated to localize the area under stress.

The major contributions of the paper are highlighted below:

- Integration of IoT and drone multispectral data for crop health monitoring. Both these sensing modalities generate heterogeneous data which not only varies in nature (i.e. observed parameter) but also has different temporal fidelity. The spatial resolution of these methods is also different, hence, the optimal integration of these sensing modalities and their implementation in practice are addressed in this paper.
- Development of crop health maps for enhanced visualization of the stressed areas and their subsequent validation through ground survey.
- Development of IoT sensors data maps which provided insights for identifying the factors affecting the crop health.

This multi modal integration of data for crop health mapping differentiates the proposed work from the existing work. Most of the existing technology based solutions in agriculture domain are either based on IoT data or remote sensing data, but the proposed system exploits the benefits of both technologies to provide a better solution.

The rest of the paper is organized as follows, the related work is described in section-2, the proposed system is discussed in section-3, the methodology is detailed in Section-4; results are discussed in Section-5, and conclusion and future work is discussed in section-6

II. RELATED WORK

Agriculture sector has evolved with the emergence of the information and communication technology. Several attempts have been made to improve the crop productivity and minimize the loss by using the modern technology [7], [10]. There are several agricultural applications based on Remote sensing in which reflective analysis of spectral bands [8] is performed using multiple VIs which provide useful insights about the health of the crops. The most common VIs are NDVI, Soil Adjusted Vegetation Index (SAVI), Enhanced Vegetation Index (EVI), and many others. Typically, the satellites used for agriculture monitoring are Landsat, QuickBird, Envisat, SPOT 6 & 7, Sentinel 1 & 2, and MODIS [11].

In [12], an automated system for monitoring the cotton crop based on IoT has been proposed to acquire the data in real time. The proposed automated system comprised the deployment of wireless sensor network (WSN) in the cotton fields for the monitoring and recording the health status of the crop. For this purpose, the Waspmote agriculture sensor board has been used which consisted of temperature and humidity sensors, soil moisture sensors and leaf wetness sensors. The main aim of the proposed system was to take proactive and preventive actions to reduce the losses due to diseases and insects/pests attack.

Crop irrigation is the primary building block of any agriculture system. therefore, there is a need of a proper water management system for irrigation purposes to minimize water loss. For this purpose, this paper [13] recommends the use of Wireless Sensor and Actuator Network (WSAN) for the crop irrigation and control by developing an in-house design and development of WSAN and its communication protocol.

In [14], a framework for modern farming using various techniques such as IoT, big data and mobile computing, has been discussed. Through this model, the farmer can be enabled to obtain information related to the needed fertilizers from the soil samples. The farmers are then informed about the total fertilizer requirement through a mobile app.

In [15], [16], the soil moisture sensing is discussed which is one of the frequently used methods by farmers to schedule irrigation. The purpose of this study was to make a low-cost and low power IoT system based on Arduino, where soil moisture sensors (Watermark 200SS sensors) were placed in the field to send data wirelessly using LoRa technology. These type of IoT based systems are known as Internet of under ground Things (IOUT). The system was effectively validated on the study site by deploying the sensors at 4 different depths in a wheat field. The advantage of the proposed system was that it provided the proof of concept of an affordable real time data gathering and analysis system for soil moisture monitoring and showed a great potential for a system that can be widely used by farmers. An IoT based system for insects detection in plants was discussed in [17]. Similarly, another IoT based system was presented in [18] in which images were processed for disease detection; while soil moisture sensor and humidity sensors were used to monitor water requirements.

The research work presented in [19] describes the use of an inexpensive low altitude remote sensing platform, GreenDrone, developed for monitoring the Maize crop. This platform consisted of a large durable fixed wing air frame mounted with a Canon camera and the FLIR thermal camera for the computation of the indices such as Normalized Difference Vegetation Index (NDVI) and Water Stress Index (WSI). There were a number of flight missions that were run to scan the study area during various development stages of the crop. The collected images were used to generate the NDVI and NGB (Near infrared Green Blue) images, which helped to delineate the regions with low yield potential, areas with variable plant counts, and identify uneven distribution of nitrogen and water management related problems.

Similarly, in another study [20], a crop health monitoring system was developed by using WSN and drone technology. The key contribution of this paper is the construction of run time clusters of sensors by taking into account the factors such as run time data acquisition, the area of interest to be scanned, absence of adequate number of nodes, and dynamic flight path of drone. In addition to this, Bayesian classifier was used to identify the most appropriate node as a cluster head. The proposed system was validated by simulating results through various software tools, and conducting experiments in labs and in agriculture field using concept devices. The results produced were supportive in terms of installation time, energy ingestion, response time and its usability.

Remote sensing systems based on satellite are suitable for large arable land because of their wide area coverage, however, their long revisit time and coarse resolution make them unsuitable for certain agricultural application where rapid response is required such as disease mapping, pest detection etc. To overcome these limitations, drone platforms were used which provided high resolution imagery on frequent basis but their power limitations do not allow them to cover large fields in a single flight mission. In addition to this, IoT based systems provide real-time statistics about crop health such as climate variables which have a significant impact on the crop health but owing to their high deployment and maintenance cost, these systems are preferably suitable for small and medium sized agriculture lands.

There are various smart agriculture systems which are based on hybrid approach and incorporate IoT, remote sensing, machine and deep learning as discussed in [21]–[23]. Nexus to this, a smart irrigation system using deep learning is presented in [24] where the research work is based on developing WSN comprising of several sensors. The data collected from these sensors is sent to the cloud where a deep learning architecture 'Long and Short Term Memory (LSTM)' is applied to predict different features such as soil temperature, humidity and air temperature. The projected values of these vital parameters helped to determine the crop best suited to be grown for subsequent season.

In addition to the application of deep learning in IoT based smart systems, deep learning is widely used in very complex agricultural activities such as weed detection, crop disease mapping, identification of pest attack, plant phenology analysis, crop yield prediction, crop classification and many more as discussed in [25]–[29]. In order to perform the above

TABLE 1. Comparison of proposed system with existing systems.

Precision Agriculture Systems	Drone data	IoT data	Multi-source data integration	VI maps	Health maps	IoT data maps
IoT based expert system for smart agriculture [12]	✗	✓	✗	✗	✗	✗
Irrigation Control using Wireless Sensor and Actuator Network (WSAN) [13]	✗	✓	✗	✗	✗	✗
Low-cost IoT system for monitoring soil water potential [14]	✗	✓	✗	✗	✗	✓
Internet of underground things in precision agriculture [15]	✗	✓	✗	✗	✗	✓
Advanced Farming Using Smart Technology [16]	✗	✓	✗	✗	✗	✗
WSN for monitoring of insects and health of plants [17]	✗	✓	✗	✗	✗	✗
Smart irrigation system and plant disease detection [18]	✗	✓	✗	✗	✗	✗
Greendrone Uas system for maize crop monitoring[19]	✓	✗	✗	✓	✗	✗
UAV-Assisted Dynamic Clustering of WSN for Crop Health Monitoring [20]	✓	✓	✗	✗	✗	✗
Deep learning and IoT for smart agriculture using WSN [24]	✗	✓	✗	✗	✗	✓
Identifying Weeds Using High-Resolution UAV Imagery [29]	✓	✗	✗	✗	✗	✗
UAV–WSN system for intelligent monitoring in PA [33]	✓	✓	✗	✗	✗	✓
IoT-based drone for improvement of crop quality in agricultural field [34]	✓	✓	✗	✗	✗	✗
Proposed system	✓	✓	✓	✓	✓	✓

activities, the most common deep learning techniques are Convolution Neural Network (CNN), LSTM, Recurrent Neural Network (RNN) and Region based CNN (R-CNN) [22]. Similarly, another application of CNN is presented in [30], in which wheat yield is estimated by detecting and counting wheat spikes. An important area of precision agriculture is to accurately estimate the area under pest or disease attack. Therefore, R-CNN is used to accurately localize the area under disease attack as presented in [31]. In addition to this. LSTM is also used for disease detection in potato plants as discussed in [32].

There are several studies in which WSN or IoT is used along with drone technology. Toward such end, an intelligent crop health monitoring system is presented in [33], in which a collaborative approach of UAV and WSN is used. The drone and WSN were used to collect images and real time data respectively. This paper was mainly focused on drone trajectory planning to collect WSN data. The collected data from WSN is transmitted to the cloud and processed by the end user. Subsequently, soil & temperature maps of the study area are generated. Although, the data is collected from multiple sources; but it is not combined together to produce a unified output. In [34], several applications of drone based agricultural systems are proposed where multiple sensors are mounted on the drone to collect multi source payload including real time data of different crop related parameters and spectral data. This research work is only focused on proposing the architectures of agriculture applications and does not provide any implementation detail of the proposed architecture and data processing.

A comparison of the existing and proposed work based on the important parameters such as ‘Drone data’, ‘IoT data’, ‘Multi-source Data integration’, ‘VI maps’, ‘Health maps’ and ‘IoT data maps’ is given in the Table 1. The comparative analysis of the previous research work has revealed that the IoT and drone data have been used separately to infer crop health status but the integration of these two modalities have not been highlighted in the recent research. However, to provide rich representation of crop health, the integration of these two modalities to generate crop health maps would be very useful. In this regard, we propose a multi-source data integration approach that combines IoT and drone technology to provide an improved crop monitoring system. Both these sensing modalities generate heterogeneous data which not only varies in nature (i.e. observed parameter) but also has different temporal fidelity. The spatial resolution of these methods is also different, hence, the optimal integration of these sensing modalities and their implementation in practice are addressed in the proposed system. Additionally, machine learning approaches and deep learning architectures [6] are applied on the combined data to generate crop health maps which provide more detailed and clear visualization of stressed areas as compared to traditional NDVI maps. Moreover, IoT sensors maps are generated which help to correlate the factors affecting the health of the crop. The proposed system has provided a technology based solution in comparison to the traditional practices in vogue and would be useful for the agricultural and research community.

A. STUDY AREA

The study area selected is National Agriculture Research Center (NARC) which is located at 33.67°N, and 73.13°E in Islamabad, Pakistan. Figure 1 shows the study area map of NARC. This map is generated using 'ArcGIS' software and the shape file is retrieved from the open source platform 'Diva-GIS'. The average temperature of this area is 21.74°C and average annual rainfall recorded is 1142 mm. The major crops harvested in this region are wheat, maize, and mustard etc.

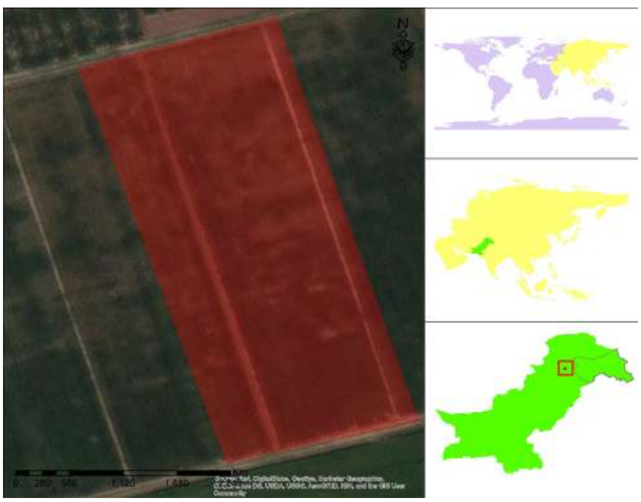

FIGURE 1. Study area map (NARC, Pakistan).

The crop selected for this research work is wheat. It is a Rabi crop which is generally sown in October-November and harvested in April-May depending on the temperature and the soil type. The life cycle of the wheat crop spans over different stages of development as shown in Figure 2. The wheat field was selected at NARC for this research work. In the trial area of 4200m^2, the wheat variety, 'BORLUAG-16', was planted in 28 passes of 100 meters length. Each pass had 6 rows with inter row distance of 0.25m.

III. PROPOSED SYSTEM

We proposed an integrated system for wheat crop health monitoring. The main building blocks of the system are IoT agri nodes, communication channel for transmitting data, drone with a multispectral camera, local server for archiving data, and a web portal for data visualization. The high level system architecture is shown in Figure 3.

The detail of the above mentioned building blocks are described in the following sections:

A. DEVELOPMENT OF IoT AGRI NODES

The development of a typical IoT node primarily involves the careful selection of sensors, communication module and the power source. The details of these components for the purpose of the current research work are described below.

1) IoT SENSORS

For the proposed system, three sensors were used including air temperature & humidity sensor, soil temperature sensor, and soil moisture sensor. For recording the air temperature and humidity, 'DHT11' digital sensor was used, for sensing Soil temperature, 'DS18B20' digital sensor was selected, and for monitoring the soil moisture level, the 'Capacitive Soil Moisture' sensor was used. There are two major categories of soil moisture sensors including volumetric and tensiometric. The volumetric sensors measure the water level in the soil; whereas the tensiometric sensors measure the water potential in the soil [35]. The selected capacitive soil moisture sensors used for this research work are Grove - Capacitive Soil Moisture Sensor (Corrosion Resistant), which are volumetric in nature. They are not factory calibrated, therefore, the optimal calibration of these sensors is a challenge. This issue is addressed by manually configuring the sensors in the lab and field using multi-point calibration technique [36].

On the other hand, volumetric soil moisture sensors which are factory calibrated are more accurate but at the same time they are expensive as well [37] and deploying such sensors in numbers are beyond the budgetary provisions of the pilot studies.

The capacitive soil moisture sensor outputs an analog voltage level which is inversely proportional to the moisture content. This sensor is sensitive to the variation in temperature, salinity and pH content of the soil. The calibrated IoT sensors' measurements were fairly accurate and this was validated by comparing the readings with the commercial sensors provided by NARC.

2) COMMUNICATION MODULE

The purpose of the communication module is to reliably transmit the data from one end to the other, and plays a key role in characterizing the performance of the system. For our research work, the 'LoRA' (Long Range) communication module was found more suitable owing to its long range

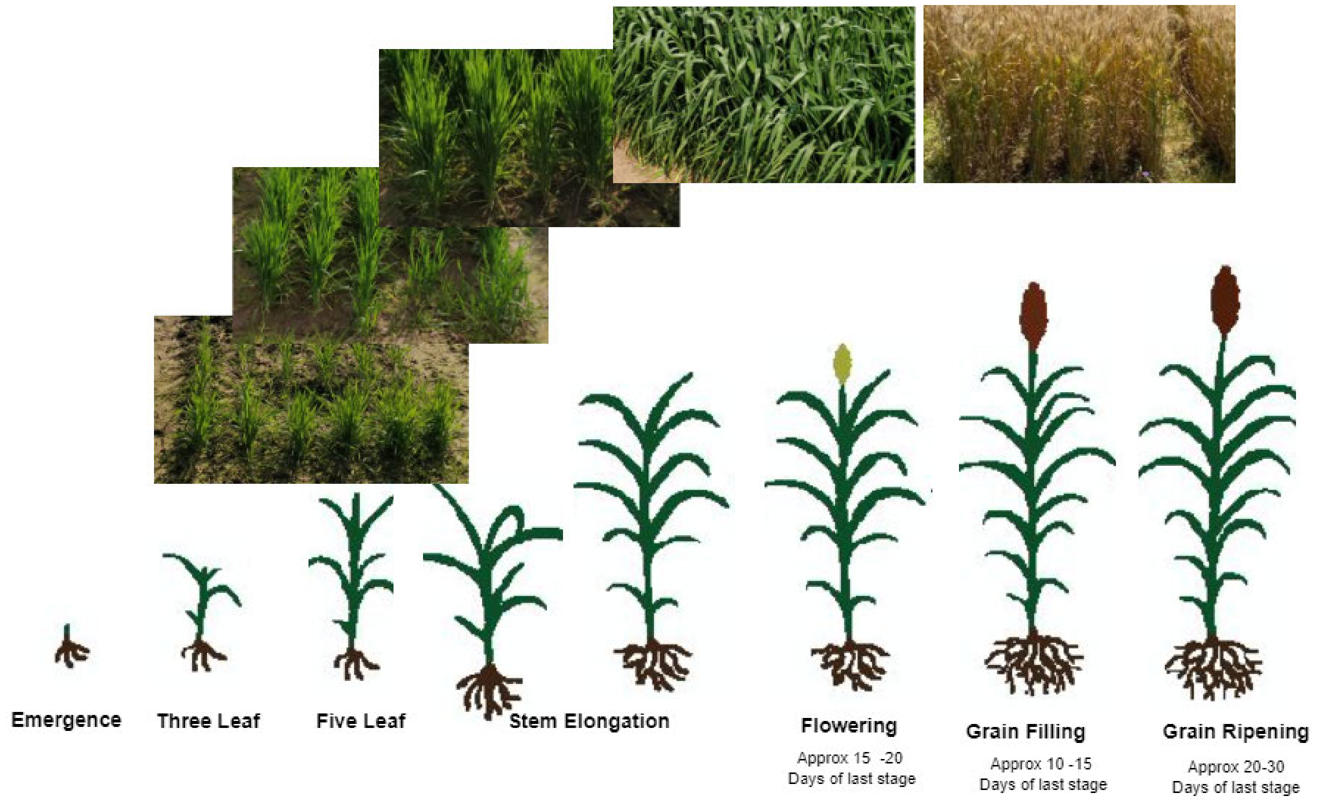

FIGURE 2. **Wheat growth stages.**

of transmission. Moreover, in an agriculture land, there is a clear line of sight which makes LoRa technology to be more effective for such a set up. The LoRa modules operate on two types of frequencies i.e. 433MHz and 868MHz. For our application, the 433MHz frequency module was used as this frequency band is license free, however, the 868mhz ISM band is not free in Pakistan. The LoRa modules use their proprietary modulation techniques in which data is sent using Chirps and they can also be interfaced with the micro-controller over the serial-parallel interface (SPI) protocol.

For the transmission of data, the IoT agri nodes were configured using star topology, which has 8× slave nodes and 1× master node. The slave nodes sent data to the master node using LoRa technology whereas, the data from the master node to the web portal was sent using GSM technology. The advantage of star topology is its cost effectiveness, however at the same time, it has a single point of failure as well. This is because a single master node is responsible for sending data that is collected from all nodes to the local server. In order to overcome this limitation to a certain extent, the SD card was placed on the master node for storing the data for 24 hours in case of any communication failure at the master node end.

3) POWER MODULE

In the IoT based systems, the continuous provision of power is the primary concern to keep the system operational for real time monitoring. The most rich source of energy for powering the proposed agriculture system is the solar energy. For this purpose, the slave nodes are powered by a 10W solar Panel and 4Ah Battery to provide long battery backups in case of rain fall and cloudy weather. The master node is equipped with 40W solar panel with a 5Ah battery to provide adequate power to it. The Figure 4 shows an IoT Agri node with LoRA and power module.

B. SYSTEM DEPLOYMENT

The IoT agri nodes are deployed across the wheat field in a star topology as shown in Figure 5.

The field is divided into a 3 × 3 matrix comprising of 9 cells where the area covered by each cell is 0.15 acres. We have deployed one IoT node in each cell to collect IoT sensors data. Each IoT node consists of sensors along with other components as shown in Figure 4. These IoT nodes cannot be deployed in bulk due to budget constraints of this research work. So, we have chosen a small experimental plot and made deployment topology accordingly. In each cell, we have recorded multiple readings by placing IoT node at different locations. On average, the readings of temperature and soil moisture did not vary significantly. Although, the information regarding the soil moisture for the given crop field can be increased by deploying more IoT nodes in each cell, but for the preliminary study, we have deployed

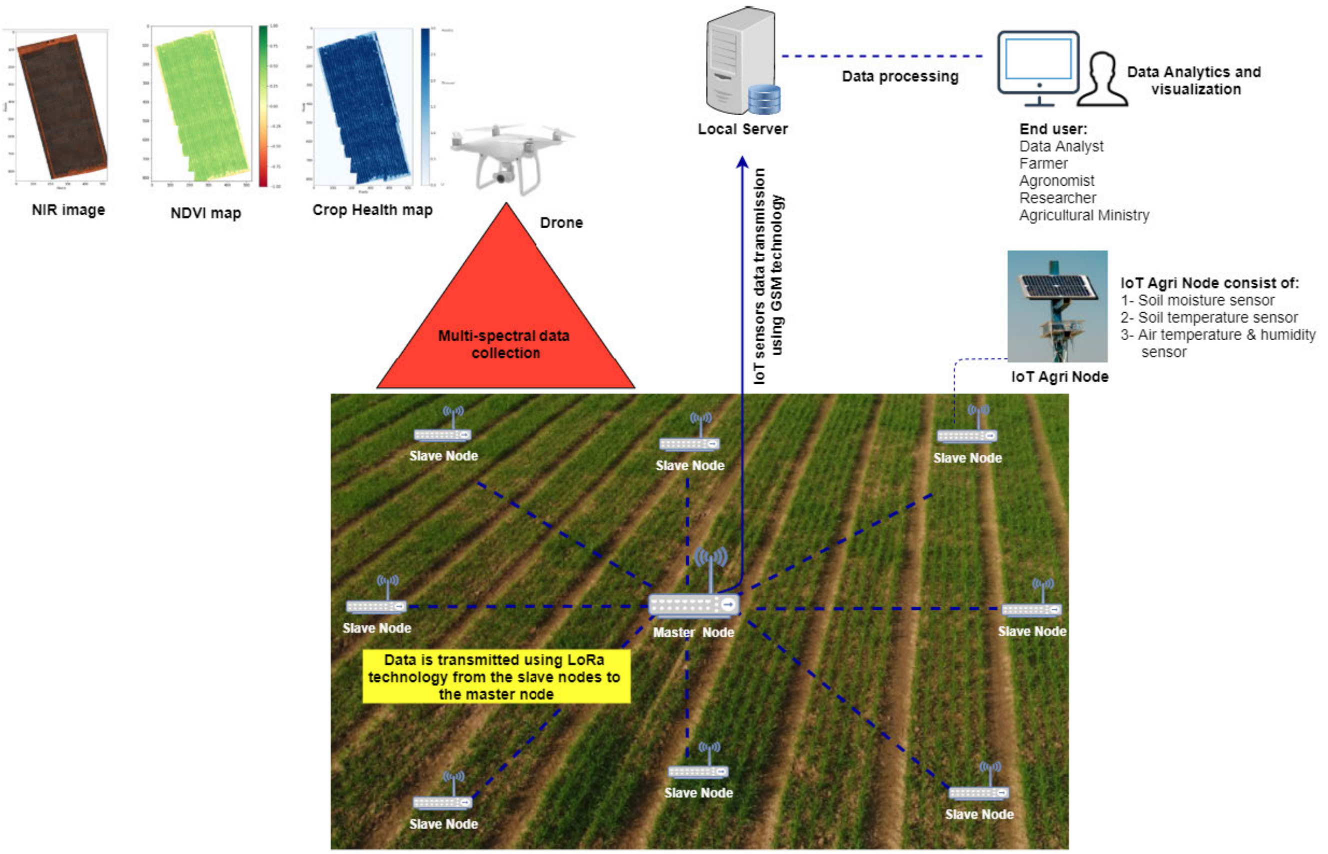

FIGURE 3. **Proposed system architecture.**

FIGURE 4. **IoT Agri Node with its components.**

9 nodes to cover the subject area. In future, we may add more sensors and adopt the robot technology for data capturing. The agriculture robot will be like a moving trolley which will move across the field and collect sensors data.

IV. METHODOLOGY

In order to develop our proposed system, the multi modal data obtained from IoT nodes and drone imagery was integrated in order to get a detailed picture of the crop health. The data from two different modalities was generated at a variable temporal resolution, which was further mapped to a fixed sized representation for data processing and analysis.

The optical and multispectral images were collected by DJI Phantom 4 advance drone with Sentera multispectral imager mounted on it. The specification of drone and the on-board imager are given in the Table 2 and Table 3 respectively.

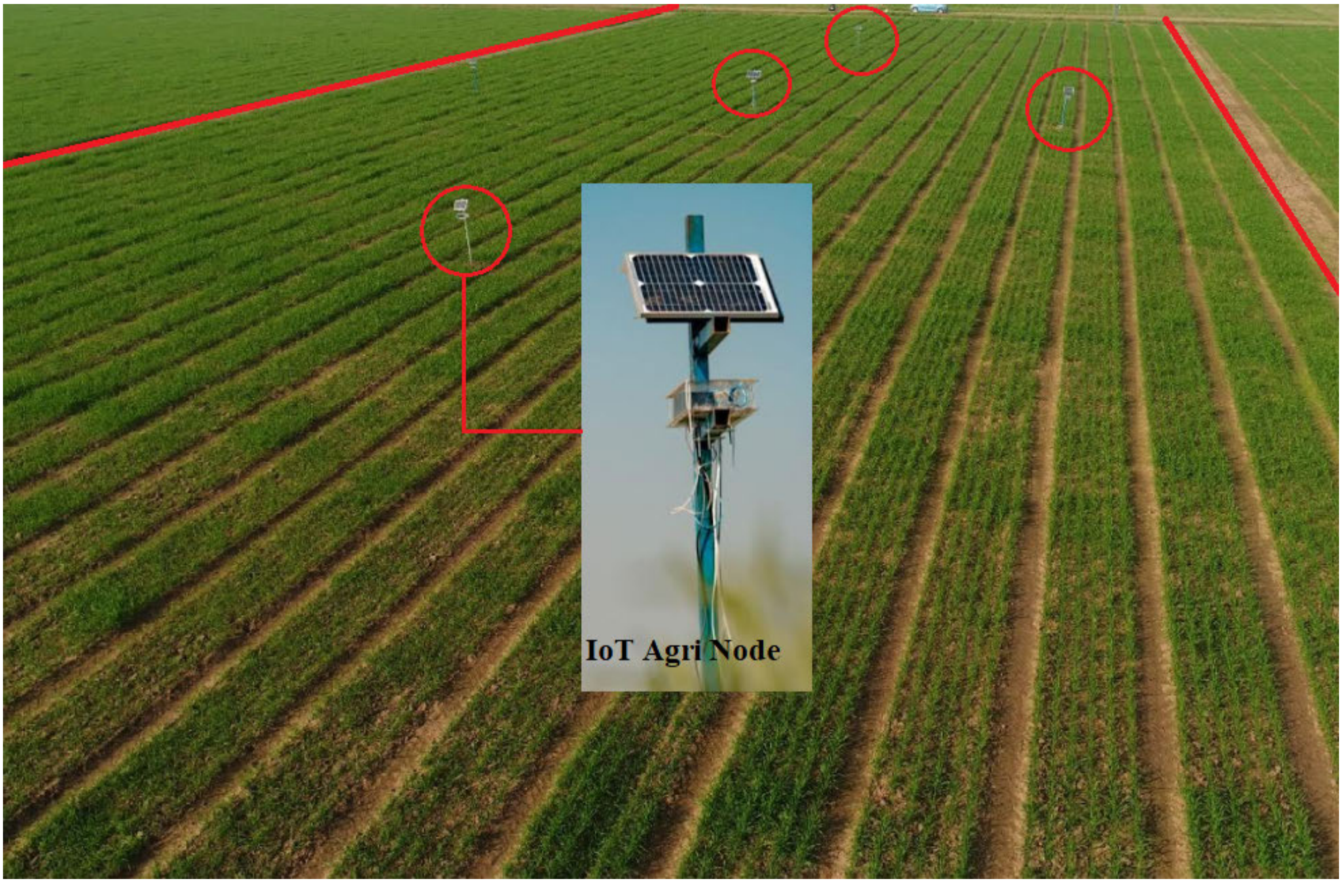

FIGURE 5. IoT Agri Nodes deployed across the wheat field.

TABLE 2. Drone specifications.

Feature	Detail
Weight	1368 gram (including propellers and battery)
Maximum flight time	30 minutes
Maximum wind speed resistant	10 meters/second
Operating voltage	7.4 V
battery type	LiPo 4S
Maximum battery charging power	160 W
Camera sensor	1 CMOS, 20 megapixels
Field of View (FOV)	Forward: 60°(Horizontal), ±27°(Vertical) Downward: 70°(Front and Rear), 50°(Left and Right)
Image size	3:2 Aspect Ratio: 5472 × 3648 & 4:3 Aspect Ratio: 4864 × 3648 & 16:9 Aspect Ratio: 5472 × 3078
Maximum battery charging power	160 W
Altitude	120 meters (recommended)
Data storage	Stored into SD card

Subsequently, various machine learning and deep learning algorithms were applied on the fused data for crop health classification and generating health maps. Later on, the health maps were compared with the NDVI maps and IoT sensors data maps for validation purposes. The block diagram representing various modules of the proposed system and the sequence of data flow among them is shown in Figure 7, whereas the details of each processing step is described in the following sub sections.

A. DATA PRE-PROCESSING

The data was collected from two heterogeneous sources including IoT agri nodes and drone, where the data from IoT nodes was sent to the local server with an interval of 5 minutes

TABLE 3. Drone imager and image specifications.

Feature	Detail
Weight	30 grams
Resolution	CMOS, 1.2 megapixels
FOV	60° horizontal / 47° vertical
Pixel size	3.75 micro meters
Focal Length	4.14 micro meters
Pixel count	Horizontally 1248; Vertically 950
Voltage range	5V to 40V
Spectral Bands	NIR, Red

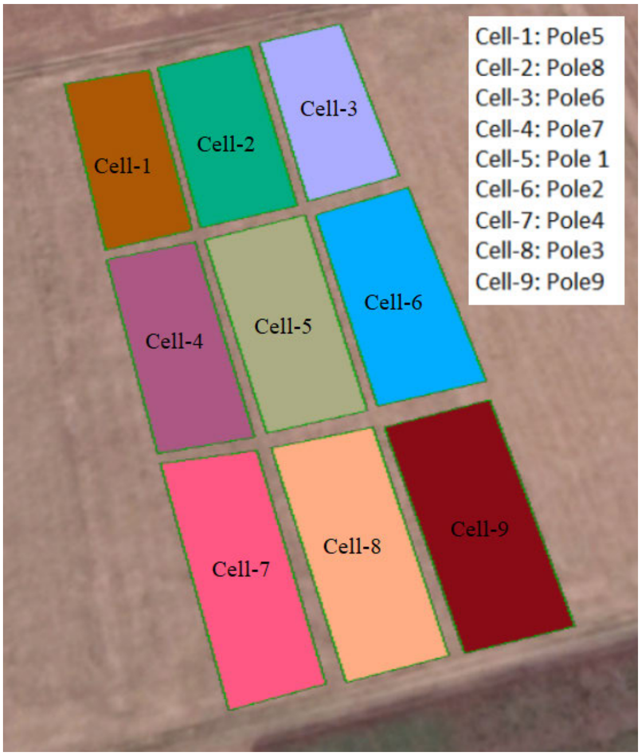

FIGURE 6. Layout of Wheat Field in the form of 3 × 3 matrix.

and drone imagery was collected on weekly basis. The IoT nodes were powered by solar panels, however in an event of cloudy or rainy weather conditions, the batteries were not sufficiently charged. As a result of this, the data was not sent to the web portal leading to missing values, which were then interpolated by using bi-linear interpolation. When the batteries restored their charge, the data transmission was resumed. During the first few minutes of the resumption of the power supply, the sensors were reconfigured and consumed some time to stabilize. During this interval, the transmitted data was considered as an outlier because the values did not correspond to the true values of the environmental parameters, therefore, the outliers were removed from the data set. In order to pictorially represent the statistical summary of all IoT agri nodes data in terms of monthly mean, variation, min-max values and outliers, the box plot was used as shown in Figure 8.

The two whiskers in Figure 8 show the minimum and maximum values of a particular variable whereas the line in the box shows the mean of the particular variable; and the black circles show the outliers, which were removed later from the data set. A distinct variation over the period of three months has been observed for humidity, which was mainly attributed to the weather fluctuations in the year 2019-20. Similarly, in the box plot of soil moisture, it has been observed that its values were increased gradually ranging from 10% to 90%. This observed behavior of soil moisture is due to the fact that during the initial crop growing stage, the soil moisture was less, however, as the crop grew in size, the soil moisture increased incrementally. It was observed from the air temperature box plot that the behaviour of the temperature profile is negatively correlated with the humidity data. The variation in the air temperature was also credited to the changes in the weather conditions. During the month of December and January, the crop was typically covered by frost and dew drops in early morning. Due to these factors, the soil temperature rapidly dropped ranging from 5°C-15°C which eventually increased in the soil moisture.

In addition to the IoT nodes data, the multispectral data was also pre-processed. For capturing the multispectral images, the drone was flown at the recommended height of 120 feet with speed of 6 miles per hour. These recommendations were provided by the multispectral imager vendor, i.e Sentera. With these configurations, the ground sampling distance (GSD) was 1.2 inches per pixel. GSD can be computed by using the Eq 7 [38].

$$GSD = \frac{\alpha \times h}{f} \tag{1}$$

where 'h' is the altitude of the platform; 'f' indicates the focal length of the image sensor and α refers to the size of the charged coupled device (CCD) cell of the imager.

There was no cloud cover in the recorded imagery as the drone is typically flown below the cloud height. On average, 25 to 30 images were captured in a single flight mission with an overlap of 70% in the image content. This overlap was then used to stitch the images seamlessly in order to obtain the complete scene representation.

B. NDVI MAPS

It is mentioned earlier that we have 9 × IoT agri nodes deployed in the field (see Figure 6), therefore, the stitched image obtained during the pre-processing stage was mapped onto these 9 cells as shown in Figure 10.

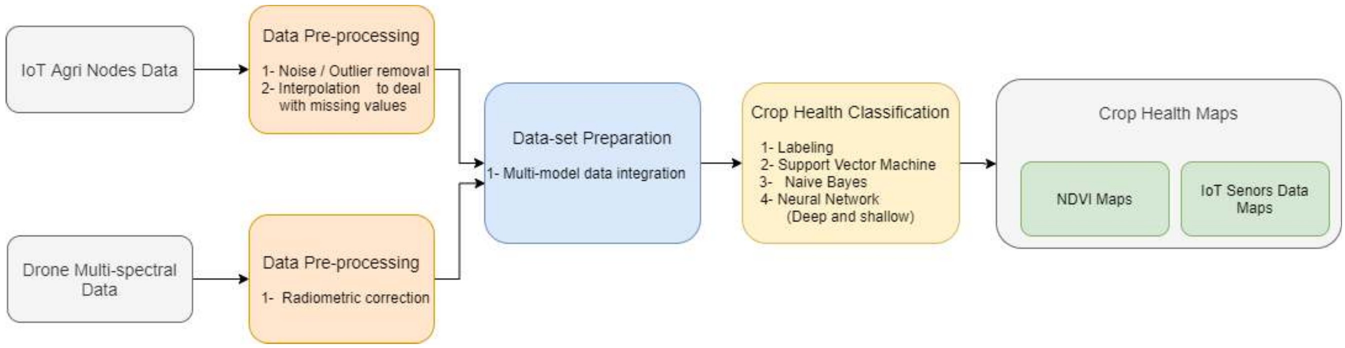

FIGURE 7. Block diagrams of the data processing.

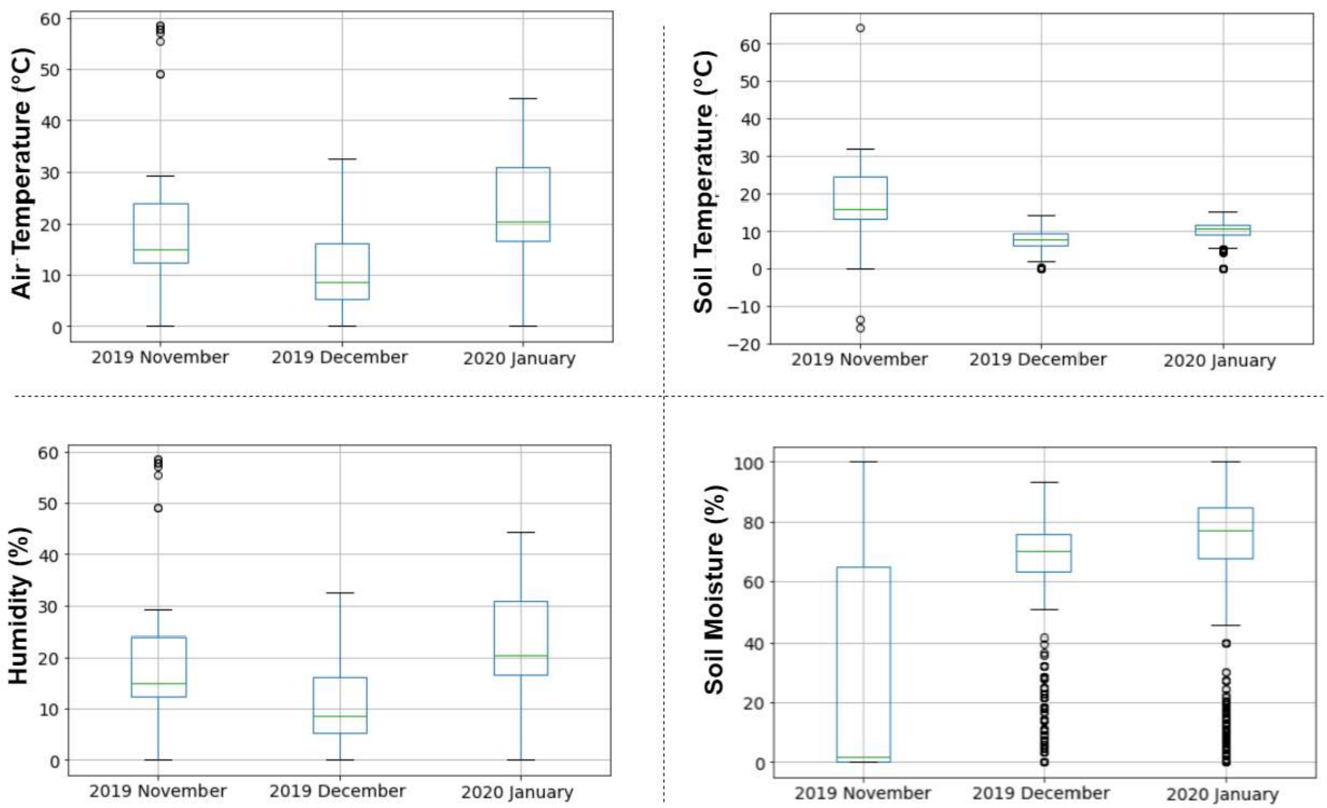

FIGURE 8. Statistical summary of IoT agri nodes data.

The NDVI values of the stitched images were computed to find the chlorophyll content of the crop. which is an indicator of the crop health status. The NDVI of the stitched images was computed using Eq 2 [39].

$$NDVI = \frac{NIR - R}{NIR + R} \tag{2}$$

where, 'NIR' is the Near Infra Red band and 'R' is the Red band.

Typically, the NDVI profile for the entire wheat growth cycle represents a parabola as shown in Figure 11.

The dotted bounding box in Figure 11 is representing the months for which we have collected the data and generated the NDVI maps. It can been seen in Figure 11 that during the early stages of crop development, the NDVI value is low as compared to the matured stage of stem elongation phase, and again a decline in NDVI values is observed during the grain ripening stage, when crop turns golden and loses the chlorophyll content.

The spatial NDVI maps generated for the period of three months starting from November to January are shown in Figure 12. The NDVI map for the month of November did not cover the entire field due to an unstable drone flight. However, NDVI maps for the other months include the complete region of the study area (Figure 12).

The area covered by the cells in Figure 12 showed the variations of NDVI at different development stages of wheat. In the Figure 12-A, the yellow color is representing sparse

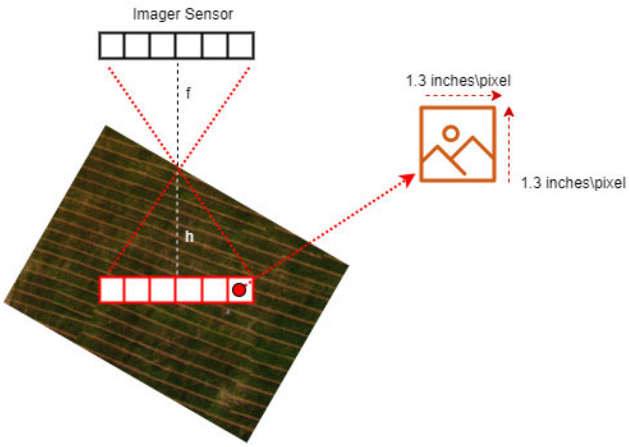

FIGURE 9. Ground sampling distance at a specific height.

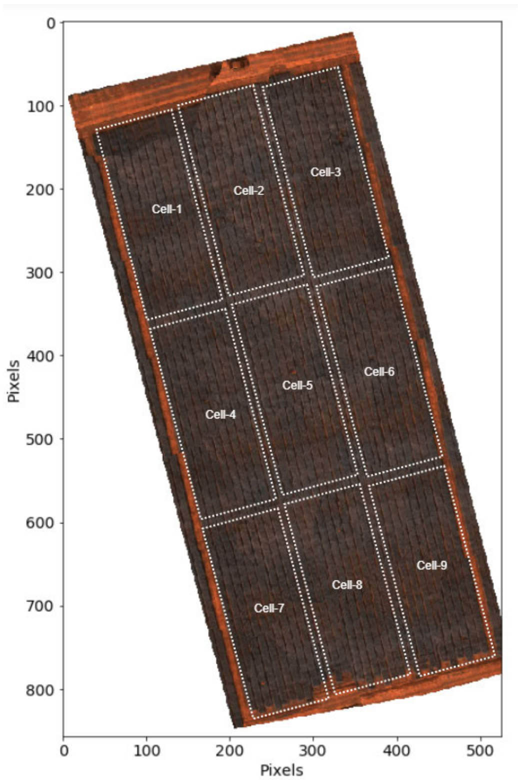

FIGURE 10. Stitched NIR image.

vegetation, while, the Figure 12-B shows the dense vegetation of crop because the plants canopy and height was relatively matured during the month of December. The yellow color in Figure 12 -A is attributed to early stages of crop development when the vegetation is low and sparse. It does not indicate the Unhealthy status of the crop at this stage. The red color shows the presence of the bare soil. In comparison to Figure 12-B, the Figure 12-C represents more yellowish content which indicates that the crop was under stress. This comparison is marked by ellipses, drawn on the Figure 12-B and Figure 12-C. Generally, in all three images, the spread of the wheat plant canopy is thin in some regions, while thick

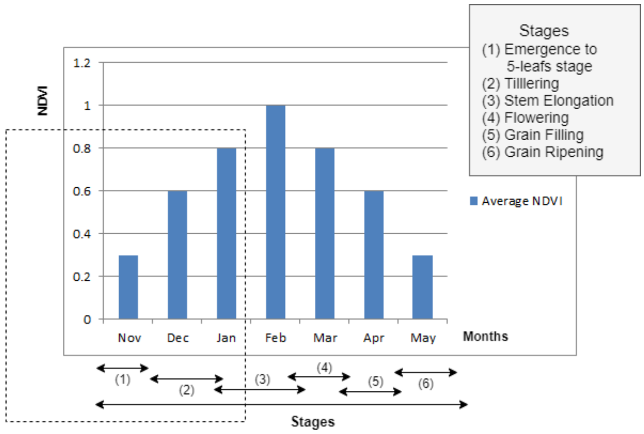

FIGURE 11. NDVI profile of entire growth cycle of Wheat crop.

in others. The crop is in the stem elongation stage which starts after 5 leafs stage (Figure 2) and lasts until the end of February. The height of the crop in this stage is not uniform across the field i.e. low in some regions and high is other regions. The green color in the NDVI image represents the region where the crop is more dense and taller. The variation in the crop height and its thickness over our the study area is mainly attributed to several factors such as the sunlight reaching to that plant, fertilizer distribution in that area, and the terrain slope to hold the water in that region.

The advantage of NDVI maps is that they provide an overall picture of crop health and help to identify the crop under stress. However, they provide limited information regarding the stressed area. These maps do not identify the sources of stress, for instance, rust disease, lack of soil moisture, extreme weather conditions, evapotranspiration, insufficient fertilizer etc. Therefore, a ground survey was performed to validate the results of NDVI maps and the visual inspection has shown that the stressed areas indicated by NDVI maps were present in the crop field.

NDVI is not the sole criteria to determine the crop health because it only indicates the presence of chlorophyll content in the plants. However, additional information and knowledge regarding the crop growth is required to determine its health status. This includes information about meteorological parameters such as air temperature, humidity, soil parameters such as soil temperature and soil moisture information, and knowledge about the crop development stage. For this purpose, the maps of the data obtained from IoT sensors were also plotted to relate them to the NDVI maps and to draw some useful inferences as discussed in the following section.

C. IoT SENSORS DATA MAPS

To analyze the variations in the crop health illustrated by crop NDVI maps, the IoT sensors data was utilized to highlight the environmental events impacting the crop health. For this purpose, the atmospheric and soil parameters maps were generated as shown in Figure 13.

These maps showed cell wise variation in the atmospheric parameters (air temperature and humidity); and variation in

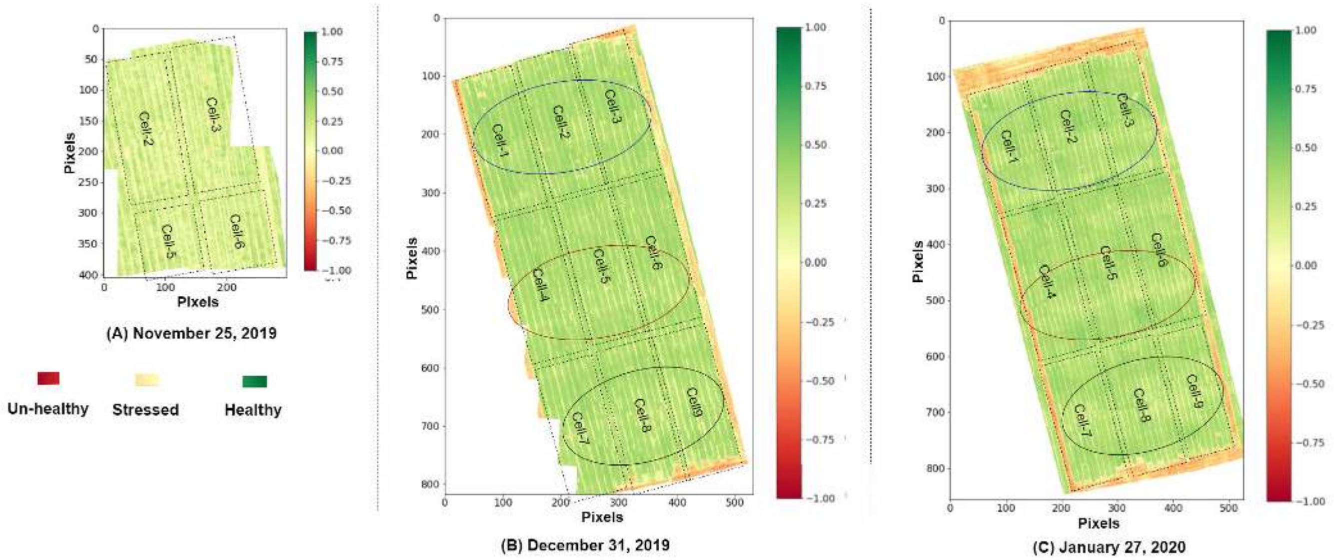

FIGURE 12. Spatial NDVI maps.

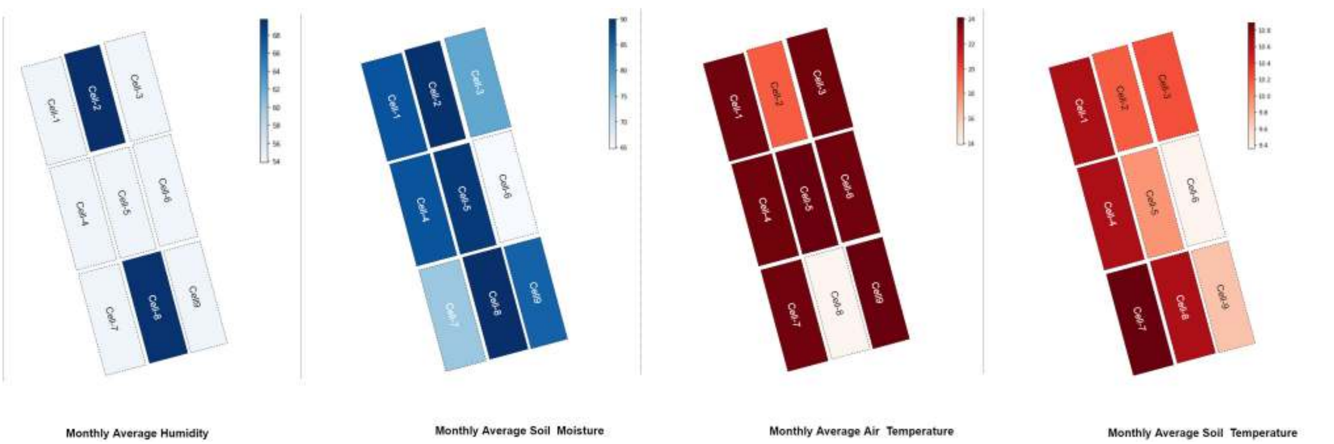

FIGURE 13. Soil moisture map, soil temperature map, humidity and air temperature map (January 2020).

the soil parameters (soil moisture and soil temperature). The variation in the NDVI maps directly corresponded to the changes reflected in the IoT data. For instance, the area covered by the cell-8 in Figure 12-C corresponded to the area under stress which was due to high humidity and soil moisture as shown in Figure 13. Consequently, the wheat growth was effected and the leaves of the crops turned yellow due to excessive moisture and low temperature. The ideal temperature requirement is 22°C at this stage (as mentioned by NARC agriculture experts), however, the recorded average temperature was 16°C, which has consequently suppressed the crop growth across the study area.

There were several other factors that effected the crop growth such as terrain slope, fertilizer distribution across the field, type of the soil, and the seed quality. The terrain surface of the study area was not uniform & smooth and varied across each cell. This is noticeable in the soil moisture map (cell wise) as shown in Figure 13-A. It is observed in cell-5 of Figure 13-B that the terrain was uneven and the dip in the ground caused the runoff water to be accumulated for a longer period of time. This has increased the soil moisture more than the crop required at this stage which caused the crop to go under stress. It is clear from the above discussion that the IoT sensors data provided added information to better comprehend the NDVI maps and helped in assimilating the reasons for the stressed crop.

In the view of above, this multi source data (IoT sensors, NDVI, and crop development stage) was subsequently integrated to generate more detailed crop health maps as discussed in the following sections.

D. MULTI-MODAL DATA INTEGRATION

In multi modal data acquisition, the data is generally produced from heterogeneous sources at variable intervals and of variable length. This multi source data is mapped to a common temporal resolution for integration and further processing. In our focused research, the IoT data was logged at an interval of 5 minutes owing to the infrequent environmental changes. Likewise, in order to discern the incremental growth of the crop, the drone imagery was recorded after every week. In order to combine the data of these different modalities, the IoT nodes data was averaged over 7 days and mapped to the temporal resolution of the multispectral imager data.

After equalizing the temporal resolution, the next step was to map the two different data set on the same the spatial resolution. The NDVI values obtained at a given crop development stage of each cell of the 3 × 3 matrix layout (see Figure 12) were flattened into a vector, where, the index of the vector represented the NDVI value of each pixel. This was further mapped to the corresponding IoT agri node data, where each record of IoT data consisted of air temperature, humidity, soil temperature, soil moisture and the temporal information of crop development stage as shown in Figure 14. The same process was repeated for each cell of the 3 × 3 matrix layout of the field. The final data set comprised a matrix $[X]_{i,j}$, where i represented the no. of records and j denoted the no. of features, which include IoT sensors data, NDVI values, and information related to the crop development stage. Once the data has been integrated and prepared for the entire crop field, it was labeled record wise to perform crop health classification.

NDVI	Air Temperature	Humidity	Soil Temperature	Soi l Moisture	Stage
0.638814	18.57	71.58	10.43	80.29	2
0.598336	11.44	77.58	9.09	30.37	2
0.367383	19.05	72.85	18.88	59.93	1
0.615248	19.32	58.78	11.38	56.85	2
0.398616	15.39	77.52	11.55	93.4	2
0.631616	11.44	77.58	9.09	30.37	2
0.657566	11.88	77.44	8.45	82.03	2
0.636019	12.47	75.77	9.45	72.93	2
0.692972	15.35	70.87	8.85	80.34	3
0.633055	11.44	77.58	9.09	30.37	2
0.681739	11.88	77.44	8.45	82.03	2
0.632761	11.44	77.58	9.09	30.37	2
0.459053	12.47	75.77	9.45	72.93	2
0.684333	11.44	77.58	9.09	30.37	2
0.670063	11.88	77.44	8.45	82.03	2
0.50365	15.39	77.52	11.55	93.4	2
0.528257	15.39	77.52	11.55	93.4	2
0.659449	11.88	77.44	8.45	82.03	2
0.489339	15.39	77.52	11.55	93.4	2
0.465149	15.6	70.46	11.54	57.66	2
0.669104	16.37	67.81	9.5	78.78	3
0.536643	15.48	70.96	11.74	59.46	2

FIGURE 14. **Format of multi modal data set in the context of the proposed system.**

E. CROP HEALTH CLASSIFICATION

For crop health classification, the data was categorized into three classes i.e. 'Unhealthy', 'Stressed' and 'Healthy'. The labeled vector was transformed into one-hot encoding since we were dealing with a multi-class problem [40]. Thus, a separate label matrix $[Y]_{i,k}$ was generated where i = no of records and k = no of classes. The final classification data set $[X]_{i,j}$ included $i = 570408$ and $j = 6$, where i was total number of records and j indicated the total features including NDVI values, crop development stage and data of IoT sensors. Subsequently, the data set was split, where 2/3 data set was used for training and 1/3 data set was used for testing purposes. As a result, the training data set comprised 382173 records and test data set contained 188235 records. The distribution of the records for three classes in the training data set i.e. 'Unhealthy', 'Stressed' and 'Healthy' was 36,904, 137,887, 207,282 respectively. Similarly, for the test data set, the distribution of 'Unhealthy', 'Stressed' and 'Healthy' classes was 18379, 68336 and 101520 records respectively.

In order to perform crop health classification, several classification models were tested including Naive Bayes (NB), Support Vector Machine (SVM) and Neural Network (NN) [22], [41], which were found suitable for the nature of the collected data. The NB is a supervised classification algorithm which uses Bayes theorem based on probabilities to classify the distinct objects. Whereas, SVM is a classifier which uses kernel function to generate highly discriminant classes with significant margin [42]. For this research work, SVM was trained using 'Radial Basis' as a kernel function.

The NN was trained using different shallow and deep learning models with different hyper-parameter settings including the (i) selection of hidden layers,(ii) hidden nodes in each layer, (iii) activation function, and (iv) loss function. Table 4 shows the design and hyper-parameter configuration of different NN models. The Figure 15 shows the architecture of NN.

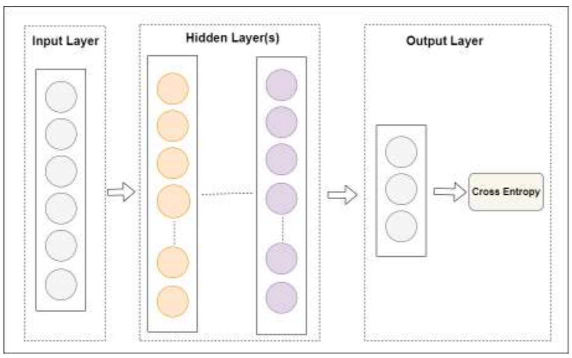

FIGURE 15. **Neural Network architecture.**

For this research work, cross entropy is used as a loss function in NN because it minimizes the difference between predicted and actual values in classification problems. This function is computed by using Eq 3 [43].

$$Cross\ Entropy = -\frac{1}{N}\sum_{i=1}^{n} y_i \log(\bar{y}_i) \tag{3}$$

where N is the total number of records, y_i is the actual label (ground truth) of i_{th} record, and $\bar{y}_i$ is the predicted value of i_{th} record computed by a classifier.

The above mentioned classification models were applied on our multi modal data set and the obtained results are discussed in the following section.

TABLE 4. Hyper-parameter configuration of different NN models.

NN Model	Hidden Layers	Hidden Nodes	Activation Function	Loss Function
M1	0	0	Softmax	Cross Entropy
M2	1	64	ReLu, Softmax	Cross Entropy
M3	1	164	ReLu, Softmax	Cross Entropy
M4	2	64,64	ReLu, ReLu, Softmax	Cross Entropy
M5	2	128, 128	ReLu, ReLu, Softmax	Cross Entropy
M6	3	64, 64, 64	ReLu,ReLu, ReLu, Softmax	Cross Entropy
M7	3	128, 128, 128	ReLu, ReLu, ReLu Softmax	Cross Entropy

TABLE 5. Performance of all classification models.

Model	Test Accuracy %	Precision	Recall	F1-Score
NB	84	83	84	83.49
SVM	78	67	76	71.22
M1	62	60	62	61
M2	96.1	96	96	96
M3	96.5	96	95	95.45
M4	**98.4**	**98**	**97**	**97.49**
M5	96	95	96	95.5
M6	94.8	93	94	93.49
M7	94.2	90	94	91.95

V. RESULTS AND DISCUSSIONS

In this section, before discussing the classification results, the various metrics used to evaluate the performance of the applied machine and deep learning algorithms will be described.

(1) Accuracy

Accuracy defines the capability of the model to generate the correct number of predictions for the observed values. it defines how close a measurement is to a true or accepted value. Accuracy is measured by Eq 4, where TP denotes to true positive, TN denotes to true negative, FP denotes to false positive and FN denotes to false negative [44], [45].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{4}$$

(2) Precision

Precision refers to the closeness or reproducible correctly classified instances of a given positive class out of the total classified instances of that class. It is calculated with the formula shown in Eq 5, where TP denotes to true positive and FP denotes to false positive [44]–[46].

$$Precision = \frac{TP}{TP + FP} \tag{5}$$

(3) Recall

Recall refers to the proportion of the total instances of a particular positive class that were correctly classified. It is calculated with the formula shown in Eq 6, where TP refers to true positive and FN refers to false negative [44]–[46].

$$Recall = \frac{TP}{TP + FN} \tag{6}$$

(4) F1 Score

F1 score is calculated to find a balance between precision and recall, because individually, they do not cover all aspects of the accuracy. F1 score is a function of precision and recall and is calculated using the Eq 7. It ranges between 0 and 1. The higher the score, the better the accuracy [44]–[46].

$$F1Score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{7}$$

A. CLASSIFICATION RESULTS

The classification algorithms (mentioned in sub section IV-E) were applied on the multi modal data set encompassing input data from drone imagery, IoT sensor data, and temporal information of the crop development stage. The performance evaluation of these classification algorithms is listed in Table 5.

It was observed that model M1 exhibited the lowest performance as compared to others because it has no hidden layer, which made it unsuitable to learn complex structures for the subject data. The models M2 and M3 had one hidden layer with 64 and 128 nodes respectively, which also led to under fitting i.e. the model was too simple to learn complex relationships in the data.

The model M4 outperformed all other classification models and showed the highest accuracy, precision, recall and F1 Score. The models M5 to M7 were less accurate relative to M4 due to their highly complex structure which resulted in over fitting. This was owing to a large number of hidden layers with excessive number of nodes. This configuration of the model decreased the performance of the classifier on the test data set as it memorized the structures in the data set instead of generalizing it.

The performance of NB and SVM models was found to be between the highest and the lowest performing models i.e.M4 and M1. Typically, SVM classifier performs better on the large data set with multiple dimensions (features), while

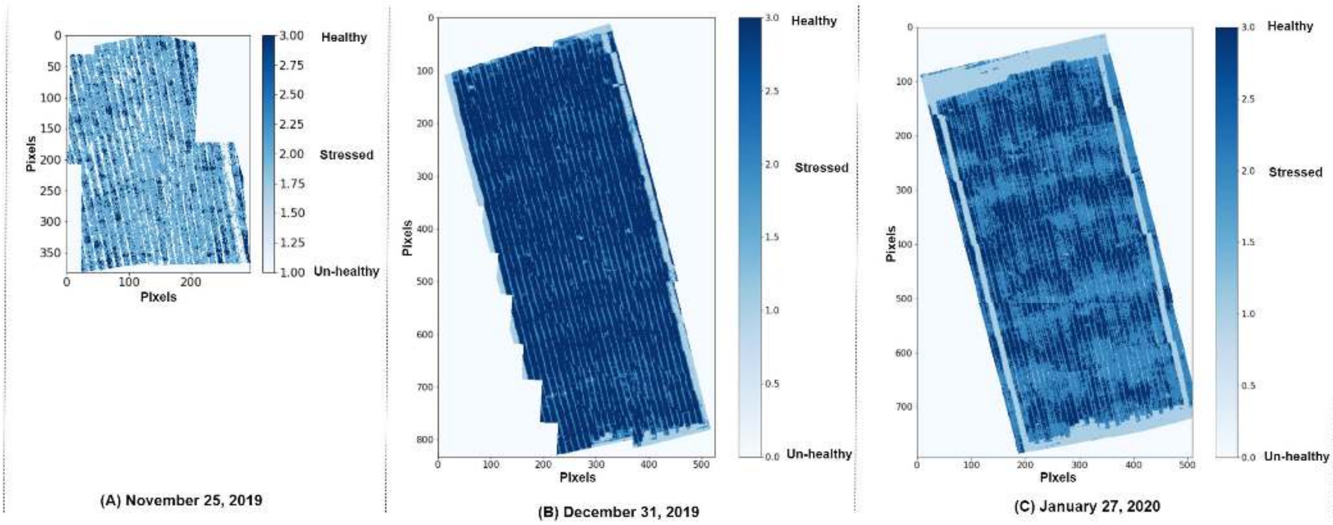

FIGURE 16. Spatial crop health maps.

NB provides probabilistic predictions on muti-class problems. Hence, these characteristics have made these models suitable for our current data set.

We can conclude from the above discussion that the crop health can be classified using multi modal data by applying machine and deep learning models. The comparative analysis of all classification models has revealed that M4 is the most optimal model among all the selected models. This model was then used to generate the crop health maps as discussed in the following section.

B. CROP HEALTH MAPS

To overcome the limitation of the NDVI maps for crop health assessment, the spatial crop health maps were generated at different crop development stages. These health maps represented the crop health status into three main categories including 'Unhealthy', 'Stressed' and 'Healthy' as shown in Figure 16. For generating these maps, pixel wise crop health classification was performed using the model M4. Each pixel was classified into three classes and was numerically labeled, where 1 referred to 'Unhealthy', 2 referred 'Stressed' and 3 referred the 'Healthy' pixels. This classification was mainly based on NDVI and IoT nodes data along with the temporal information of the crop. The tagging of this multi source data set into three classes was performed with the help of NARC agriculture domain experts. Subsequently, the health maps were generated (as shown in Figure 16) after applying the M4 model of NN on this multi modal data set. The gradient in the blue color of Figure 16 represents the three classes of crop health as shown in the color legend.

It is clear that the health maps in Figure 16 provided a distinctive and improved visualization of crop health status as compared to the health information shown in the NDVI maps in Figure 12. The stressed and Unhealthy areas shown in Figure 12-C can be seen in more detail in Figure 16-C. There was no reference data available to validate the crop health maps, therefore, ground survey was performed and agriculture specialist were consulted for this. The validation of the above results have supported the hypothesis formed earlier in section I, which stated that the integration of multi modal data can enhance the representation of crop health information as compared to the crop health status depicted only by NDVI.

VI. CONCLUSION & FUTURE WORK

A system for crop health monitoring has been proposed which is based on integration of the latest technologies such as drone based remote sensing, IoT and machine learning. The integration of these sensing modalities generate heterogeneous data which not only varies in nature (i.e. observed parameter) but also has different temporal fidelity. The spatial resolution of these methods is also different, hence, the optimal integration of these sensing modalities and their implementation in practice are addressed in the proposed system.

The multi-modal data was collected from different sources including IoT sensors and drone with a multispectral camera mounted on it. This multi source data was generated at variable intervals and of variable length. This data was then mapped to a common temporal resolution for integration and labeled to perform supervised classification. The machine learning techniques such as SVM and NB along with several deep learning models were applied to classify each pixel as healthy, Unhealthy or stressed. Among these selected models, M4 model of NN was found to be the most suitable model for our multi-modal data set and provided the classification accuracy of 98.4%.

Conventionally, NDVI is used for monitoring crop health but it only provides the health information based on chlorophyll value, whereas, for a detailed crop health representation, the data from multiple sources is required such as soil moisture, soil temperature, humidity and air temperature.

For this purpose, the data from two different modalities were combined and crop health maps were generated to provide a clear picture of the crop health relative to the information provided by NDVI maps. In addition to this, IoT sensors data maps were generated to correlate the behaviour of environmental variation with the crop status delineated in the crop NDVI maps, where these maps provided useful insights about the factors influencing the crop health. The IoT sensor data maps were validated by comparing IoT sensors reading with the commercial senors provided by NARC and they were found to provide a competitive accuracy. The crop health maps were validated through the ground surveys and agriculture experts due to the absence of reference data (such as drone imagery database of the subject area, satellite images with a compatible image resolution, and real time data generated by IoT sensors). The validated maps revealed that crop health maps based on multi-modal data provided rich insights into crop health status relative to the crop health knowledge provided by individual NDVI maps.

For the future work, the role of other parameters related to crop health will be investigated, which may enhance the performance of the proposed work. Additionally, the soil properties using multispectral data and their effect on crop health will be analyzed. Further, the fertilizer maps such as nitrogen maps will be generated to determine it's spread across the field and impact on crop health.

ACKNOWLEDGMENT

The research work has been conducted in NUST-SEECS, IoT Lab in collaboration with NARC, Islamabad.

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