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Smart Farm with Foodborne Pathogen Monitoring

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ABSTRACT— ***Conventional agriculture uses data about real-time climatic conditions, soil (texture, depth, nitrogen levels), illumination, topography, moisture, etc. to make appropriate decisions with regards to sowing, watering, fertilizing, pesticide-treating and harvesting. However, it does not have a system to monitor pathogens and collect data on the amount of pathogens present in various abiotic factors (e.g. water, soil). Due to the absence of effective techniques in detecting pathogen contamination at the farm or field level, it is currently difficult to deter a food related illness and outbreak once contamination has been introduced. The purpose of this research is to help identify contamination hazards at the farm using biosensors to detect pathogens in potential sources of contamination, such as water, soil, manure, and air. By adopting Internet of Things (IoT) connectivity, a simple farm can be turned into a smart farm. The objective of a smart farm is to prevent threats to the farming and food industry by monitoring pathogen levels and using real-time alerts to warn applicable stakeholders when established thresholds have been surpassed.***

Keywords— Biosensor, IoT, Information System,

1. INTRODUCTION

The methods for identifying and tracing foodborne outbreaks have improved over the years, which have enhanced the likelihood of identifying produce-associated outbreaks; however, being able to trace the source of outbreak at farm level instead of retail level and recall immediately will save costs.

The process of identifying where and how the contamination develops is often challenging because of the variability in diagnostic testing procedures, and the delays in result reporting and in performing epidemiologic investigations [1]. Moreover, fresh produce has a short shelf-life and may be irrelevant for lab testing after a few days. However, contamination for 20% of produce-associated outbreaks originates on the farm via contaminated water, air, or animal or human feces coming in direct contact with the plant. Once contamination is within or on the plant material, it is unlikely to be destroyed by subsequent washing and sanitizing of the produce [1]. The goal of this research is to elevate a traditional farm into a smart farm, which would help detect pathogens and contamination hazards by continuously monitoring pathogen levels in the water, soil, and air, in order to prevent further distribution and transmission of the contamination to the public.

2. PURPOSE

On average, there are approximately 800-1000 food outbreaks every year in the United States. From 2005-2015, a total of 10,075 outbreaks have been reported, causing 193,199 illnesses, 9,604 hospitalizations, and 201 deaths [2]. Foodborne illnesses and outbreaks are caused by eating food that has been contaminated by pathogens or harmful toxins or chemicals. Pathogens are microorganisms, such as bacteria, viruses, and parasites that can cause food poisoning. Norovirus, Salmonella, Listeria and E. coli are some of the pathogens that record the biggest numbers and headlines with their lethality [1].

Foodborne illnesses can be especially dangerous for vulnerable populations, such as the elderly, very young children, or those that have a compromised immune system [1]. Not only do food outbreaks cause public health issues, they also have significant economic consequences. In 2013, the mean estimate of the total annual cost of foodborne illness from Salmonella alone was $3.6 billion [3]. According to a 2015 study at Ohio State University, costs associated with medical care, lost production time, and illness-related mortality can amount to approximately $55.5 billion annually [4]. There can also be costs associated with legal actions and food recalls, but more importantly companies can incur huge losses due to reputational damage [1]. Chipotle's six outbreaks in 2015-2016 have cost them 28% of share value over a year and 7% of permanent customer base loss [5]. Blue Bell's dairy contamination in 2014-2015 resulted a $125 million loan.

[6] Implementation techniques that identify, reduce and prevent foodborne outbreaks have a potential to aid in great cost savings for public health as well as private companies.

3. FACTORS THAT CONTRIBUTE TO THE SPREAD OF ECOLI, SALMONELLA & NOROVIRUS

The pathogenic microorganisms can be introduced at farms during the pre-harvest or post-harvest stage. Sources of the pre-harvest phase include soil, manure, water used for pesticide treatment, irrigation water, and insects, while post-harvest sources consist of wash water, equipment used for harvesting and transporting the crops, human handling, dust(that of livestock farms and pollution generators residing upwind), inadequate storage, etc. Animals are a source during both stages [1].

4. PREVALENCE OF FOOD-BORNE INFECTIONOUS DISEASE

Fresh-produce (e.g. fruits and vegetables) is a prospective market of smart farm employment [7]. Based on data from outbreak-associated illnesses for 1998–2008, 46% illnesses were attributed to produce, which is higher than the percentage attributed to fish, dairy, eggs, meat, and poultry products [8].

No. (%) Illnesses (Includes overlaps)					
Commodity	All agents	Bacterial	Chemical	Parasitic	Viral
Plants	4,924,877 (51.1)	1,169,202 (32.1)	62,753 (25.2)	69,023 (29.5)	3,623,899 (65.8)
Grains-beans	435,936 (4.5)	183,394 (5.0)	12,995 (5.2)		239,547 (4.3)
Oils-sugars	65,631 (0.7)		2,344 (0.9)		63,287 (1.1)
Produce	4,423,310 (45.9)	985,807 (27.0)	47,414 (19.0)	69,023 (29.5)	3,321,066 (60.3)
Fruits-nuts	1,123,808 (11.7)	230,636 (6.3)	29,483 (11.8)	60,573 (25.9)	803,116 (14.6)
Vegetables	3,299,501 (34.2)	755,171 (20.7)	17,931 (7.2)	8,450 (3.6)	2,517,949 (45.7)
Fungi	4,542 (0.0)	686 (0.0)	3,857 (1.5)		
Leafy	2,152,652 (22.3)	188,327 (5.2)	9,113 (3.7)	7,256 (3.1)	1,947,955 (35.4)
Root	349,715 (3.6)	96,910 (2.7)	1,240 (0.5)		251,566 (4.6)
Sprout	32,703 (0.3)	32,703 (0.9)			
Vine-stalk	759,889 (7.9)	436,546 (12.0)	3,721 (1.5)	1,194 (0.5)	318,428 (5.8)

Table 1: Attribution of Foodborne Illnesses, Hospitalizations, and Deaths to Food Commodities by using Outbreak Data, United States, 1998–2008 [9]

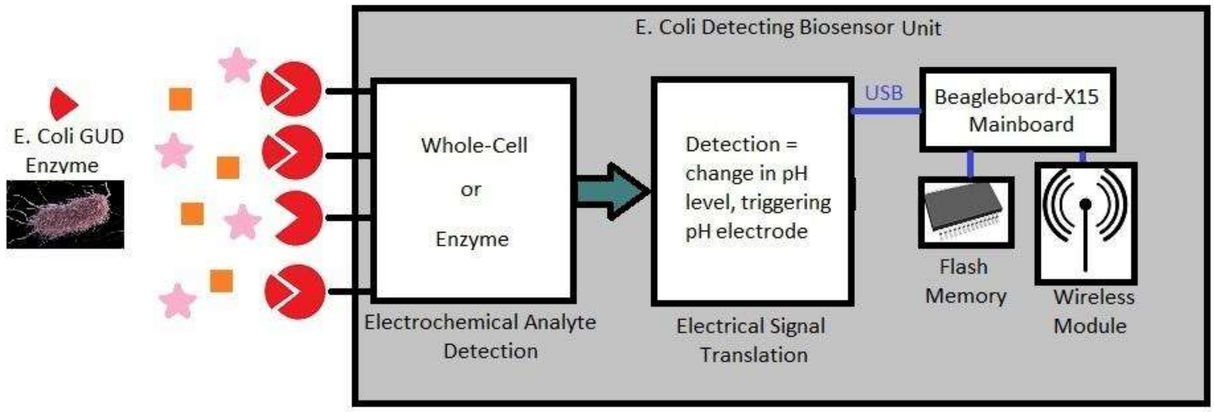

Figure 1: UML Biosensor Unit Designed to Detect E. Coli, with BeagleBoard Components

5. SMART FARM MONITORING FOR OUTBREAKS

The preferred spelling of the word "acknowledgement" in America is without an "e" after the "g". Avoid the stilted expression, "One of us (R. B. G.) thanks . . ." Instead, try "R. B. G. thanks".

5.1 Biosensor

The biological sensor, or biosensor for short, is a tiny electrical device converts a biological response into an electric signal [10]. The sensor itself contains an analyte which is pre-configured to detect for a particular biological pathogen such as a bacteria or virus. Biosensors detect the proliferation of a pathogen within minutes in: the water supply of the farm, the soil in which the crop grows, and the surrounding air.

5.1.1 Soil Sensor

Several E. Coli outbreaks can be traced to the manure used within the soil that eventually spreads to the leaf face through rain splash. The ideal positioning of the biosensors would be at the ground level and would reside alongside the growing crop. An enzyme based electrochemical biosensor would be contained within a weather resistant housing and installed at an average height of 4 inches above ground level. This height can vary depending on the specific crop being monitored; for example, a foot above ground level for corn. This device utilizes a protein based membrane specially designed with a high surface area so it can be presented with the same air that passes over the crops. Any pathogen that would normally attach itself to a crop would also embed itself within the membrane of the pathogenic analyte.

Multiple sensors would remain in the field for the life of the crop. The sensors' cartridges need to be replaced every 30-60 days but the sensors are very inexpensive and the replacement is not cost prohibitive.

5.1.2 Biosensor Unit Technology

The development of biosensor unit should satisfy constraints, reliability and cost.

The entire unit as outlined in Figure 1 would be of a size similar to a credit card and consist of the biosensor analyte and detection mechanism integrated with an ultra low-powered BeagleBoard Green (Wifi version) mainboard and CPU (1Ghz ARM processor). Beagleboard is a single-board computer that has two Grove connectors to make connection to Grove sensors easier. This allows for additional data collection outside of the standard analyte sensor. The BeagleBoard-X15 would act as the control module, connecting ultimately to a base station through wireless 802.11 technology. The onboard operating system runs a lightweight version of Unix called LiteOS. Ambient temperature, humidity, and light sensors are also onboard to gather additional data on growing conditions. Power to the unit comes in the way of 6 watt solar panel with an onboard battery pack. The onboard 6600mAh battery can power the device for over 6 days without any solar charging. This is accomplished in part from using a low power footprint and also technology which power downs the device between sensor readings.

5.1.3 Biosensor Connectivity

One of the challenges is reliable connectivity, given the vast estate these devices must cover. To affect consistent coverage, a virtual fabric of sensors may use MyriaNed (WSN) fundamentals. This allows each sensor to communicate directly to the next, where sensor readings are shared through 'gossiping'. Ultimately the communication terminates at the base station which is a full feature terminal consisting of several high powered directional antennae. This device must reside in a more permanent structure such as the farm house or barn. The base station is the cloud data repository where the data is cached and analyzed.

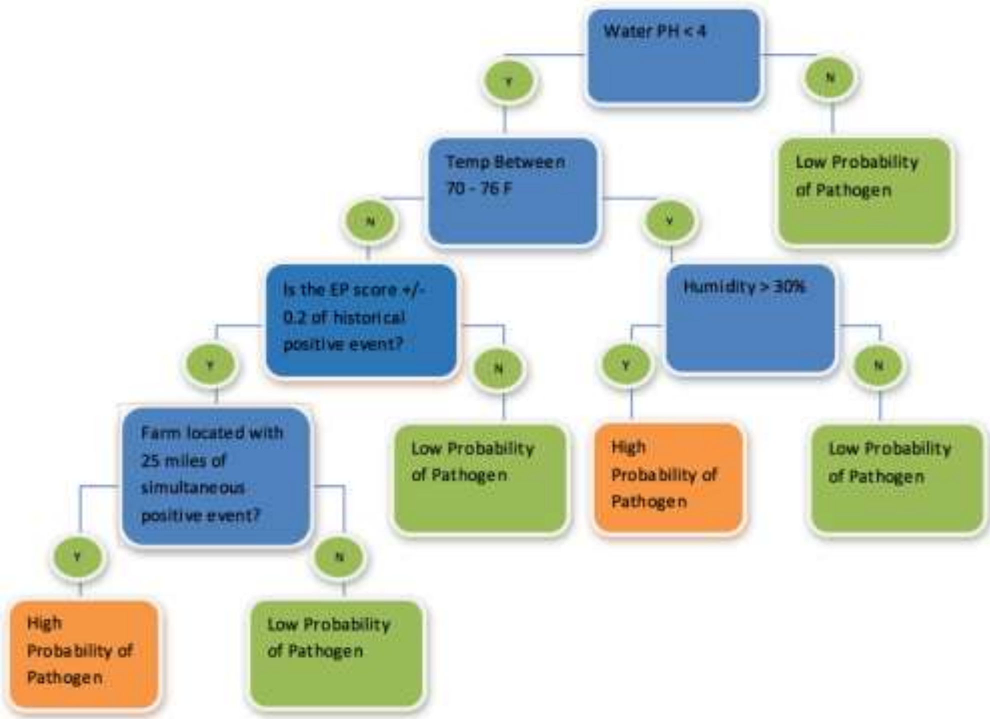

Figure 2: Heuristics Breakout Algorithm

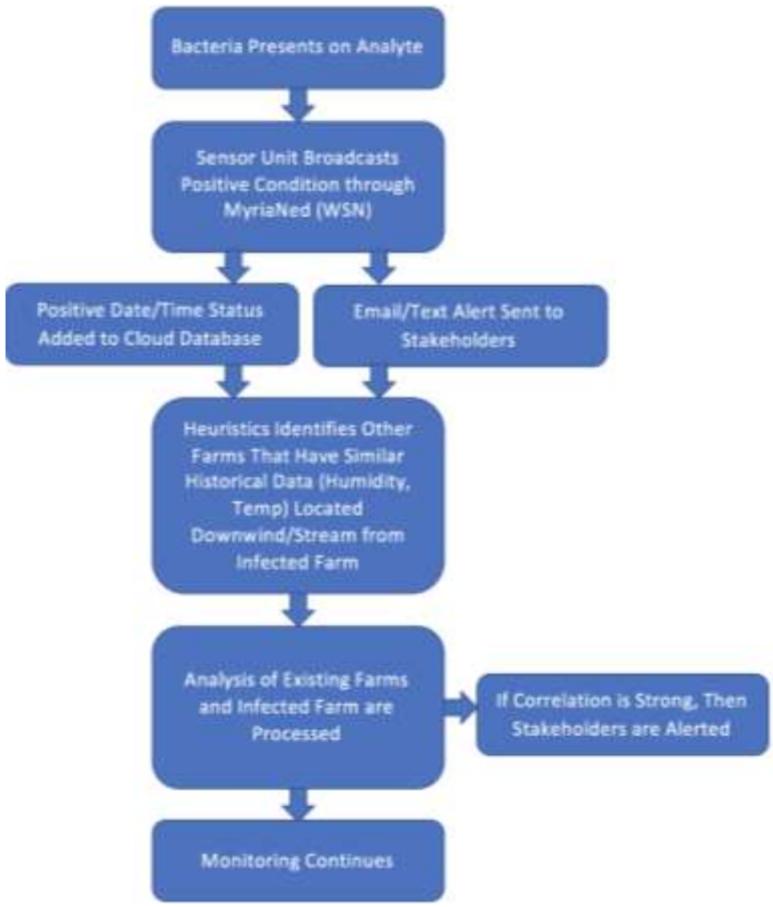

Figure 3: Positive Pathogen Event Algorithm

Figure 3: Historical Dashboard

5.2 Smart Farm Analytics and Live Reporting

A fabric of biosensors connecting reliably to the base station provides a real-time look at the current state of the farm and pathogen level. Gathering this information consistently over time will allow for data mining, reporting and also providing alerts with automated responses to anomalies.

The base stations can be maintained through MyriaNed, which can be connected with all sensors, alert as sensors go offline, and upload all collected data to the cloud. The application infrastructure takes advantage of a cloud PaaS and integration from an internet information services (IIS) web server and a SQL backend. The web front end allows for client logins and a graphical user interface (GUI), providing monitoring and reporting tools for farmers and local government agencies. Free SQL Server Reporting Services (SSRS) be used for live reporting and alerting. As thresholds are exceeded, a runtime will be initiated to alert the required parties: farmer, FDA, crop buyer, recommending a course of actions based on the type of threat and level of contamination.

5.3 Data Analytics Dashboard

A full set of heuristics can be developed which, upon a receiving a positive pathogen proliferation event, immediately starts comparing other farms downwind or downstream for data that may correlate. Figure 2 and Figure 3 outline this process. Each attribute of water pH, temperature, humidity, distance and time from other outbreaks will be weighted to equal a dashboard score which gives a simple figure for possible pathogen activity on a specific farm, denoted Effective Pathogen (EP) score. The cumulative historical data of these attributes' predictability will update the EP score according to an algorithm and this may vary seasonally. The frequency report that can be generated from these results can provide the farmers with valuable information of which crops and farms to implement extra quality assurance measures for, further lessening the probability of outbreaks and preventing the adoption of ineffective control measures.

6. CONCLUSION

This paper focuses on the innovation in: (1) an IoT based data pooling from the environment and biosensors, (2) database creation in the cloud, (3) big data analytics to detect and forecast a dangerous level of pathogen proliferation, (4) a real-time reporting to stakeholders and (5) locating the source of the outbreak's type, factor, time and location. The model is progressively refined as more attributes' characteristics are associated with the number of pathogens detected in biosensors.

Adopting a preemptive detection approach as opposed to being completely reactionary can benefit produce buyers as well as farmers. This technology is low-cost and the benefits of keeping customers healthy far outweigh any implementation costs.

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