A Multi-Agent Platform for the Remote Monitoring and Diagnostic in Precision Agriculture

T. Noulamo, A. Djimeli-Tsajio, J. P. Lienou and B. Fotsing Talla

Abstract—**In this paper, we propose a Multi-Agent system approach to build a real-time monitoring system architecture for plant disease management. Each agent is designed to perform one of the three generic functions: acquiring videos and monitoring diseases in tomato plants using neural networks, calculating a prescription in case of an attack and communicating the results to the farmer by SMS. We are tackling the question of automatic plant disease management using a network of cameras and an implementation of a set of programs to process obtained images. The proposed diagnostic agent model performs the diagnosis of tomato disease from images of tomato leaves or video from cameras installed in the farm. The extraction of the tomato leaf images in the video is done using object recognition by color. If an attack is detected after execution of the diagnostic subsystem, the information is transmitted to the prescribing agent. This agent then uses five sub-module namely User Subsystem, Search Subsystem, Validation Subsystem, Extraction Subsystem and Mapping Subsystem to process the treatment to be applied to solve the anomaly. The result of the treatment is transmitted to the farmer by the remote communication agent via SMS. The proposed architecture is not only reusable but also easily maintainable in the sense that it is possible to support new diseases with minimal configuration without modifying the source code developed in java. Experiments were carried out for disease monitoring in a tomato farm.**

Index Terms—**Remote Monitoring, Phyto-patology Diagnostic, Multi-Agent System, multi-Camera platform, Precision agriculture.**

I. INTRODUCTION

MAny industries use real-time control systems. These systems range from small scale process facilities to large-scale distributed systems. In low-income countries, agricultural development is essential for growth and rural development. Improving agricultural productivity is an effective factor in economic growth and poverty reduction, both inside and outside the agricultural sector. In [1], Xiong and Qiao reported that the integration of precision agriculture systems could be an effective way to solve complex problems in agriculture. One of the most promising subsidiaries in this sector is the tomato. The tomato is one of the most cultivated and consumed vegetables in the world because of its short production cycle with high yield and its nutritional and therapeutic properties. However, this crop faces phytosanitary problems (viruses, bacteria and fungi), which considerably reduces the production yield [2]. Faced with this situation, farmers opt for pesticides, weeding and crop rotation. But these measures are effective only if the disease is diagnosed at an early stage. 90% of diagnosis made with naked eyes, requires very advanced expertise in plant diseases and also a regular assistance from trained botanist [3].

This is one of the reasons why low-income farmers put the knowledge gained through word of mouth or by seeking advice from crop protection traders. Unfortunately, this approach usually leads to poor treatment practices. This has an impact not only on current production but also on future production. The question is therefore to know how to improve the reliability of the diagnosis of diseases without however calling on an expert in phytopathology?

With the development of new technologies, it is possible to use techniques based on artificial intelligence to automate the diagnosis of plant diseases and thus remedy the misdiagnosis. This is why we propose in this work to contribute to the remote monitoring and diagnosis of plant diseases using Multi-Agent approach. We propose in our approach an architecture which uses three agents: a diagnostic agent, which is able to identify a disease from the image of the leaves. A prescribing agent which is able to prescribe a treatment according to the diagnosis from the diagnostic agent. Finally a remote communication agent formulates a message to inform the farmer by SMS of the state of the farm.

To carry out our work, we will organize this paper as follows: This introduction is followed by a description of the Real-Time monitoring system in section 2. Section 3 will focus on the state of the art on rudimentary and automatic monitoring and diagnostic techniques in agriculture. After a brief presentation on fundamental concepts in plant disease, we will present some uses of Multi-Agent approach for monitoring and diagnosis in agriculture. In section 4, we will present the overall architecture of the monitoring and diagnostic system that we set up, from the video acquisition device to the remote communication, passing through a diagnostic and the treatment phase. Section 5 will be devoted to the explicit description of the software agents. Section 6 will cover the presentation of the results, their interpretation and discussion. We end this paper with a conclusion and perspectives for further work.

II. DESCRIPTION OF THE REAL-TIME MONITORING SYSTEM

A. Real-Time monitoring system

Production systems can be affected by defects of various kinds. A failure in one part of the process can worsen

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and cripple or damage the entire system. It is therefore essential to implement reliable monitoring techniques for these systems in order to accurately detect the appearance of signs of failure. In agriculture, the process is similar. 90% of the diagnosis is made with naked eye, requires very advanced skills in plant diseases and involves regular assistance from a phytosanitary expert. This is one of the reasons why low-income farmers apply the knowledge gathered by word of mouth or by seeking advice from the phytosanitary product seller. Unfortunately, this approach usually leads to poor processing practices, which impacts not only on current production but also on future production.

Automation techniques provide tools for monitoring systems in real-time, based on measurements taken from them. The literature offers a multitude of methods to tackle monitoring problems [4], [5], [6]. Amongst methods that exist, the monitoring method based on the parametric identification approach will retain our attention. It consists in extracting the various parameters on the monitored farm video and comparing these estimates with the known parameters' nominal values. The estimation error is used as a residue, helps to classify the data and helps to decide on the state of the area under monitoring.

B. Principle and equipment

Fig. 1 illustrates the overall principle of the proposed real-time monitoring system. It is made up of three subsystems:

- The video acquisition node consists of a set of wireless cameras, having the capacity to send the filmed images to a given station.
- The processing node, which integrates all the algorithms necessary for the diagnosis.
- The receiver is any device capable of receiving information and quickly alerting the farmer. Cell phone are such devices.

If the image transmitted by the acquisition node has a default, the processing node calculates the appropriate treatment to solve the problem and send an SMS to the farmer's cell phone.

III. Related review of literature

The design of real-time control and monitoring systems for complex system has been explored by various researchers since 1980 [7], [8].

In [9], Kenneth Birman et al. have proposed the use of a real-time system for the monitoring of the power network based on Internet communication protocols. This technological evolution has several implications for data communication systems, which facilitates the implementation of real-time algorithms. This problem has been highlighted by several researchers [10], [11], [12], [13].

In agriculture, farmers spend more time and energy, traveling between locations to monitor ongoing activities such as irrigation and phytosanitary issues such as (viruses, bacteria and fungi), which drastically reduce yield of production [14].

Advances in technology make it possible to construct and deploy a network of wireless sensors and a monitoring system to automate many of these tasks:

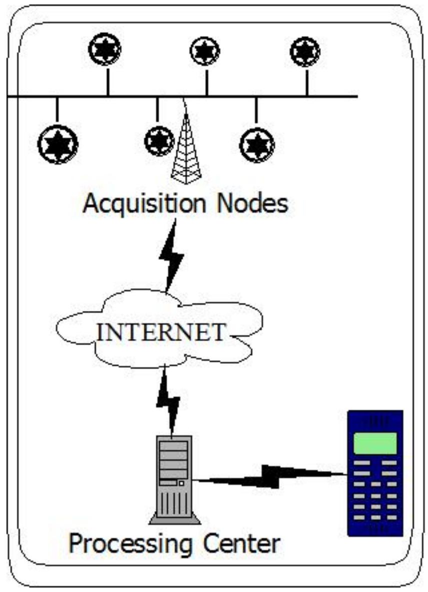

Fig. 1. Configuration of the Distributed Real-time Control System

- Agricultural practices are greatly supported by the use of sensor networks [15], [16]. In this momentum, several information technologies including satellite navigation, grid and ubiquitous computer network could make a significant contribution [17]. Thus, air temperature, humidity, ambient light, soil humidity and temperature are monitored by the authors of [18]. Similarly, Pala et al. [19] take advantage of intelligent monitoring techniques for early detection of faults in the aeroponic system.
- Laksono et al. [20] designed an array of wireless sensors and actuators for the Journal of Sensors 3, controlling, monitoring and conditioning an aeroponic growth chamber. The wireless protocol designed was based on the ZigBee technique. The proposed system integrated the sensors, actuators, communication system and database server.
- Sani et al. [21] recommended a web-based control and monitoring system for the aeroponic system. Their system was composed of micro-controllers (using Arduino IDE program), actuators (two relays include atomization spray and fan on/off on specific time), sensors (temperature and pH sensor), LDR (light intensity sensor), and communication modules (GSM/GPRS/3G modem).
- Anitha and Periasamy [22] designed wireless sensors technique to monitor the aeroponic system. The technique used the ZigBee prototype. The proposed network architecture was based on temperature, pressure, humidity, water level and pH sensors.
- Gabriel Villarrubia et al. [23] have designed Multi-agent system and Wireless Sensors Network to build virtual organizations of agents that can communicate each other while monitoring crops. The monitoring focuses on several parameters: the temperature, solar radiation, humidity, soil pH, and wind. In their approach, they propose an architecture in which each agent supports a parameter to be controlled.

The above work is concerned with atmospheric parameters such as: temperature, humidity, soil PH, wind power, solar radiation rate, etc. We are concerned in this work with pathological problems of plants caused by viruses, molds, etc.

IV. Architecture of the System

A. Multi-Agent System

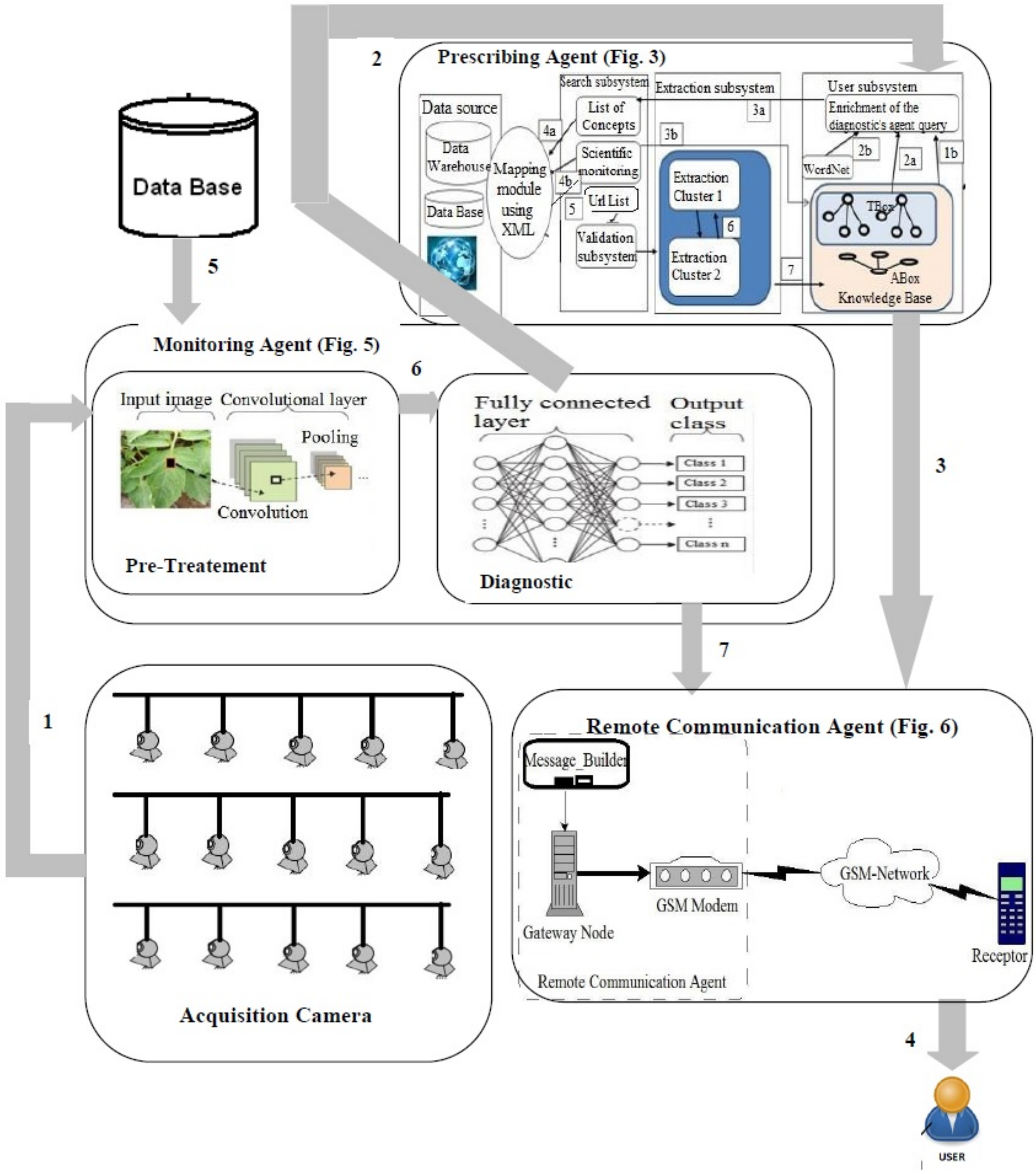

Fig. 2. Multi-Agent System Architecture

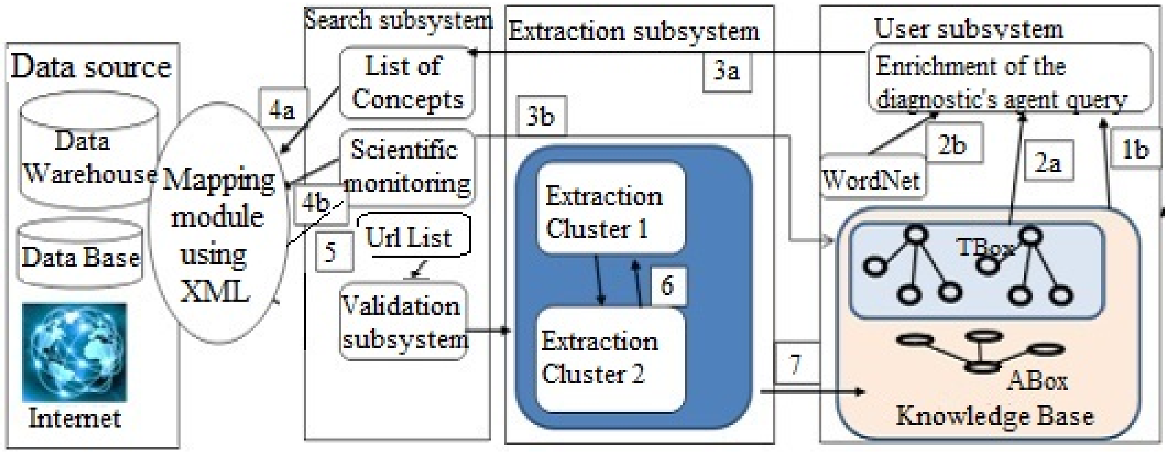

Fig. 3. : Architecture of our prescribing Agent.

The multi-agent approach is centered on the notion of interaction between the constituent elements of a model [24]. It is a collection of processes, which are executed concurrently, share common resources and communicate with each other [25]. The functionality of each agent is governed by the set of rules assigned to it. An agent can, thus, be designed to perform the function of monitoring or diagnostic depending on the rules assigned to it. In [26], John M. Hawkins proposes a control model incorporating an agent whose role is to facilitate communication between production and distribution stations in an network power control. We will present in the following paragraph the tasks expected to our agents.

B. Multi-Agent modeling the monitoring of the system

The system architecture, in Fig. 2, shows how the various sub-systems interact to produce the overall system functionality. The arrows indicate the directions of information flow between the agents. The Interactions numbered from 1 to 7 are described as follows:

- 1: Transmission of information (Video) from the cameras, implanted in the physical system, to the Monitoring Agent.
- 2: Transmission of the diagnostic results from the Monitoring Agent to the Prescribing agent.
- 3: Transmission of the therapeutic results from Prescribing agent to the Remote Communication Agent.
- 4: Transmission of the Diagnostic and the prescription message by SMS to the farmer via a GSM network.
- 5: Parameters of the MLP use to configure the monitoring agent with the data resulting from the training.
- 6: Transmission of images from pre-processing module to the Diagnostic module.
- 7: Transmission of the diagnostic results to the Remote Communication Agent.

The system is modeled as a set of agents working together to oversee a farm. Agents are classified according to their functions in the system. Our system performs three main functions: Monitoring, prescription and remote communication.

- Monitoring Agent: This agent uses two sub-modules, the Pre-processing sub-module and the Diagnostic sub-module.
  The pre-processing sub-module designed by a CNN (Convolutional Neural Network) decomposes the video received from the acquisition sub-system into a succession of images, then from each image the tomato leaves are extracted using the algorithm of Viola and Jones [27]. The images of the leaves are stored in a buffer for processing by the diagnostic subsystem. The diagnostic subsystem then identifies the disease. Here we use the Multi-Layer Perceptron (MLP) algorithms [35] to perform the classification and communicate the result to the prescribing agent. It should also be noted that our diagnostic tool uses the weights stored in the database (see Fig. 4) for its configuration.
- Prescribing Agent: The Prescribing agent has an architecture derived from that proposed by Espinasse B. et al. [33] which uses an ontology which is designed by extracting data from different data sources. The general architecture of our Prescribing agent is given on Fig. 3. When the Prescribing Agent receives the results of the diagnostic information, it makes the request to the US (User Subsystem). When launching a query with answers existing in the knowledge base, the result is returned. Otherwise (1b) the query is enriched using the concepts present in the ontology (2a). The user's query submitted to traditional search engines often ignores the underlying consensus of the domain notions. The role of the ontology is therefore to provide the consensual concepts and the relationships between these concepts. Every world synonym describing the concept (2b) is found using the Wordnet library. Once the query is enriched, it is transmitted to the Search Subsystem (SS)(3a). The SS Subsystem will scan data sources, querying existing search engines, particularly Google (4a, b). A list of URLs is channeled to the extraction cluster of the Extraction Subsystem (ES), of the knowledge sub-domain being processed (5). An appropriate recommendations are sent by the cluster concerned to other extraction clusters, in order to suggest pages likely to be of interest to them (6). The pages obtained are subject to validation by an expert. From the validated pages obtained, the interested cluster extracts the relevant concepts and the relationships between these

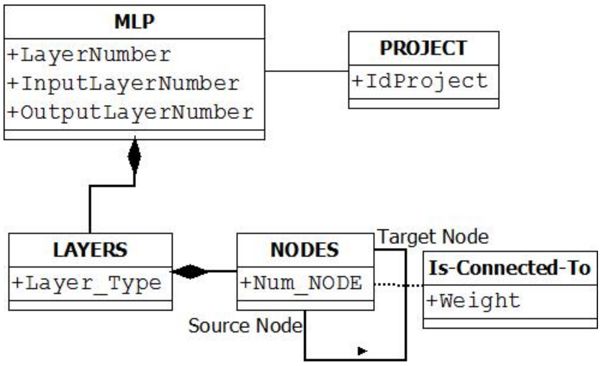

Fig. 4. Except form of the Database Model

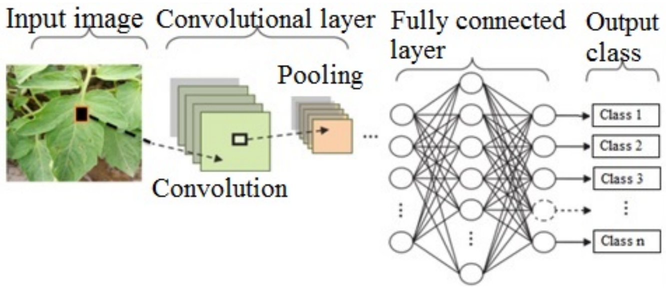

Fig. 5. : Architecture of our Diagnostic Agent.

TABLE I
DESIRED OUTPUT OF MLP

Output bits										
Position	Value									
S1	1	0	0	0	0	0	0	0	0	0
S2	0	1	0	0	0	0	0	0	0	0
S3	0	0	1	0	0	0	0	0	0	0
S4	0	0	0	1	0	0	0	0	0	0
S5	0	0	0	0	1	0	0	0	0	0
S6	0	0	0	0	0	1	0	0	0	0
S7	0	0	0	0	0	0	1	0	0	0
S8	0	0	0	0	0	0	0	1	0	0
S9	0	0	0	0	0	0	0	0	1	0
S10	0	0	0	0	0	0	0	0	0	1
Disease Identification	YLCV	TMV	Target spot	Spider mite	Septoria leaf spot	Mold	Late blight	No disease	Early blight	Bacterial spot

concepts to transmit them to remote communication agents and to populate the initial ontology, thus updating the knowledge base and facilitating future research.
In order to keep the knowledge base up to date and respond to the user without the need to process the query, we have included in the search sub-system, scientific monitoring tools, that will take care of retrieving in real time (4b), links to new publications in the target domain and returning the Urls of the pages to the retrieval sub-system. The scientific monitoring tools takes into account the context of the ontology to update the knowledge base(3b).

- Remote Communication Agent : The communication agent upon receipt of information from the diagnostic agent, constructs the message to be sent to the farmer by SMS. The message includes the identifier of the camera which sent the image, the disease diagnosed and the treatments offered.

V. SOFTWARE DESCRIPTION

A. Diagnostic agent

Several techniques are used in classification problems, methods based on computer learning algorithms [28], [29], [30]. This type of training for the problem of image classification requires a robust pre-processing. This is not trivial and is observed by lower accuracy in comparison with deep learning techniques. In contrast, the work of [31] and [32] have focused on the classification of images using deep learning. Although this method is the most appropriate, the authors obtained a still low accuracy. We propose in this paper a high precision agent approach. In the practical use of our application, images are captured from a higher definition camera. The scene is a video in which the farm is extensively depicted with the capture of all possible details of plant development. The nature of the scene being a sequence of video images, we decompose this video into a succession of images, then on each image we apply the Viola and Jones [27] algorithm for the selection of tomato leaves in the scene. To this end, a first neural network has been trained to recognize the tomato leaf of any kind among the possible objects visible in the farm. Recognition at this level is by shape and color, and the features used are obtained by transfer learning from the pre-trained ResNet101 architecture.

The Fig. 5 shows the diagnostic process of our model. We have used the pre-trained model ResNet101 and ResNet152 for the extracting of the descriptors of each image of the database. Then we use a MLP representing the fully connected layer to perform the classification. It should also be noted that at the end of the workout the classifier weights will be saved to a database for their practical use. Note that in the operation of extracting features of the plant (tomato) leaf, each convolution layer has different characteristics from the other layers, ranging from coarse information to more and more precise information as we move through the network towards the output. ResNet101 is made up of 346 levels and 105 convolution layers. The result obtained from the extraction is subjected to a classifier which in our case is a Multi Layer Perceptron (MLP) with one hidden layer. We have chosen to use 400 neurons in the hidden layer and 10 neurons for the output layer representing each class of tomato leaf disease case. Realizing that this is supervised learning, the desired output is fabricated as shown in table I.

B. Prescribing Agent

This agent uses five sub-modules namely, User Subsystem, Search Subsystem, Validation Subsystem, Extraction Subsystem and Mapping Subsystem. The User Subsystem receives the request and perform many tasks, builds the request using the diagnostic information, returns the information in the case of searching for information that has already been constructed, enriches query using the concepts present in the ontology and find in the wordnet library all

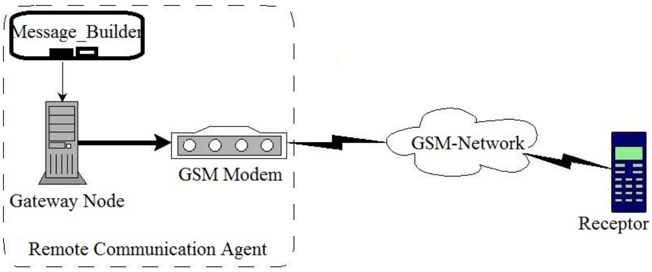

Fig. 6. : Architecture of our remote communication agent.

the synonyms of the words describing the concepts. The Search Subsystem browses data sources by querying existing search engines. The validation subsystem, from the query and the list of links obtained from the user subsystem, it proposes an interface that allows an expert in the domain to validate the found pages relevant to the query. From the validated pages obtained, the Extraction Subsystem extracts the relevant concepts and the relationships between these concepts to transmit them to remote communication agents, and to populate the initial ontology. The mapping module provides the interface between the data sources with the search subsystem and standardize the way queries are built. The extracted data is structured as an XML file and the URI is sent to the ES [34].

The modular development approach to domain ontology that we advocate in this work is of particular interest. Indeed, extraction clusters and ontology enrichment are built using specific ontology modules

C. Remote Communication Agent

The transmission of SMS between a mobile device and a recipient and vice versa can be carried out through different protocols such as SS7 within the framework of the standard GSM protocol, or even by TCP/IP with the same standard. The figure below illustrates the architecture of the communication agent that we have implemented. It is based on the GSM protocol.

From the information received from the diagnostic agent and the prescription agent, the Message Builder constructs the message to be sent and communicate it to "Gateway node" which takes care of the delivery to recipient via the SS7 protocol.

VI. Results and discussion

A. Diagnostic results

We have obtained the accuracy of $97,0\%$ for the network trained with features from ResNet152 architecture at level 515 and 97.2% accuracy for the network trained with features from ResNet101 architecture at level 345. These results are comparable with the results found in the literature. Table II shows the learning performance of different network levels with ResNet101.

Analysis of these results shows that after MLP training the features extracted at level 345 from the pre-trained model ResNet101 provided a better learning performance in term of 97.2% accuracy. We can also observe that the recognition rate increases with the number of convolution layers. However at the last layer, we observe the opposite phenomenon. This

TABLE II
Learning outcomes

N°	Level of ResNet101	Number of convolutional layers	Learning performance (Accuracy)
1	50	16	69.2
2	100	31	87.5
3	150	46	87
4	200	61	87.9
5	250	76	87.9
6	300	91	89.4
7	345	105	97.2
8	346	105	70.9

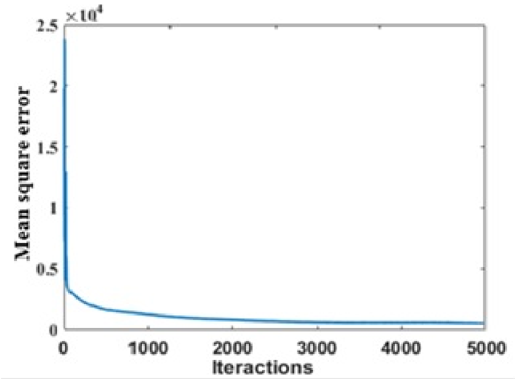

Fig. 7. : Decrease of the mean square error

conclusion has also been done for the second pre-trained model ResNet152. Fig. 7. shows the mean square error curve during training of the network with features obtained from ResNet101.

Fig. 8. illustrates the accuracy of the test set during the learning of the network with features obtained from ResNet101 at level 345.

Fig. 9. depicts a comparative study between our approach and the results of the literature. These results show that our method is accurate overall using concatenated features. Table III illustrate the performance parameters of our system for each class.

The experimental model was carried out on the images of two farms of tomatoes filmed by a higher resolution camera. Note that in each farm, an isolated experimental portion of

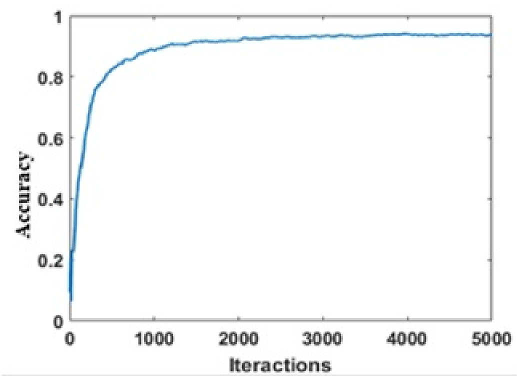

Fig. 8. : Accuracy obtained on test set

TABLE III
PERFORMANCE PARAMETERS OF OUR SYSTEM FOR EACH CLASS

Class		Mean features				Concatenated features			
N°	Name	Accu -racy	Preci -sion	Recall	F1-Score	Accu -racy	Preci -sion	Recall	F1-Score
1	YLCV	99,64	99,16	99,62	99,40	99,67	99,71	99,13	99,69
2	TMV	99,94	100,0	97,37	99,97	99,97	100,0	98,65	99,99
3	Target spot	99,31	95,37	95,71	97,30	99,42	96,34	95,99	97,86
4	Spider mite	99,53	96,90	97,81	98,20	99,37	94,60	98,81	96,93
5	Mold	99,34	97,96	95,18	98,64	99,34	95,52	97,71	97,39
6	Septoria leaf spot	99,64	97,37	95,85	98,49	99,56	96,86	94,87	98,19
7	Late blight	99,28	95,86	97,77	97,54	99,64	98,56	98,33	99,10
8	No disease	99,81	99,36	98,42	99,58	99,78	99,07	98,46	99,42
9	Early blight	99,09	93,06	91,78	95,98	99,39	95,68	92,67	97,50
10	Bacterial spot	99,78	98,54	99,51	99,15	99,72	99,07	98,61	99,40
Total (macro) for all test data set		97,69	97,36	96,90	98,44	97,94	97,54	97,32	98,55

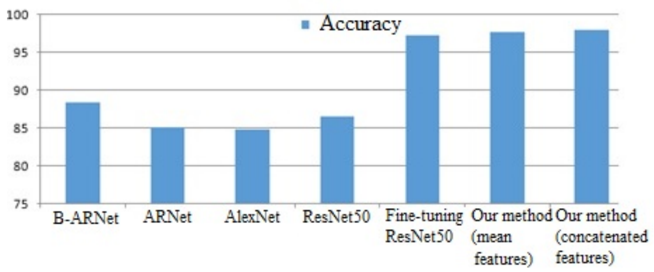

Fig. 9. :Compared study with literature results

about twenty-five tomato plants was left unattended in order to cause infections. According to the agronomist's report, the two experimental plots had been infected. The experimental results obtained from our system corroborated perfectly with those of the practitioner, namely that the two farms were healthy while the experimental plots were infected, one by tomato mold and the other by tomato target spot and bacterial spot.

Our diagnostic tool uses the weights stored in the database (see Fig. 4) for its configuration. It's possible to configure our diagnostic sub-system with different weights to solve a different problem like to monitor air temperature, humidity, ambient light, soil moisture and temperature. Fig. 11 show the interface to create a new diagnostic project.

Once the project has been created, the second phase of the generation process consists in setting the weights of the diagnostic system. Fig. 11 illustrates the case of recording a weight matrix.

B. Prescription Agent results

The functions of ontology enrichment is given below. The function of enriching the Prescribing agent's query with the concept structure of the ontology is as described on Algorithm 1. Algorithm 2 describes the search function. The extracting data procedure from the web page is given in algorithm 3.

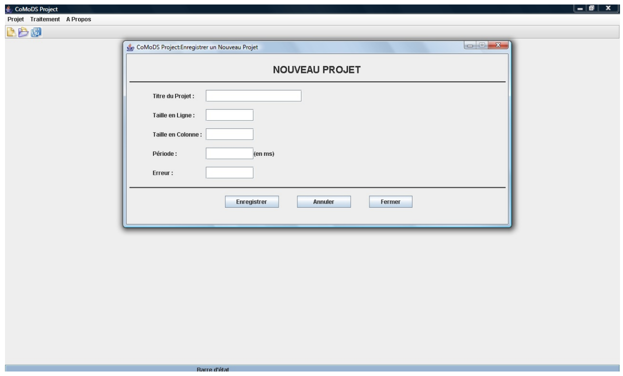

Fig. 10. : Diagnostic project creation form

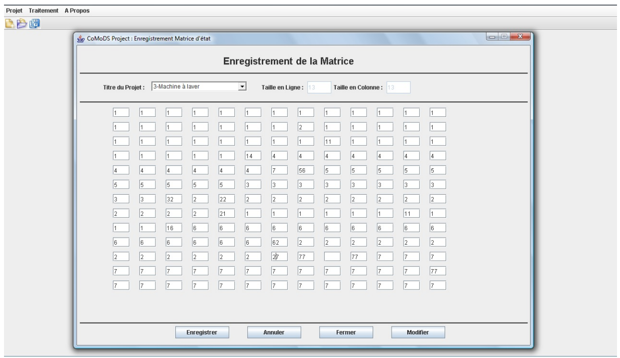

Fig. 11. : Weight matrix parameters' form

TABLE IV
ALGORITHM 1: REQUEST ENRICHMENT

	Function: enrichRequest(string)	
1	dic← convertStrgWord (string)	/*Convert the string to a word and store it in a dictionary*/
2	load(ontology)	/*Loading the ontology */
3	load(wordnet)	/*Loading the wordnet library*/
4	**For** word ∈ dic:	
5	listConcept← $c_i \in C$ Such as $c_i \in$ synset(word) or $c_i \in$ Domain(word) ∪ Range(word)	/* C set of ontology concepts */
6	**return**(listConcet).	

Algorithm 4 describes the procedure of the ontology module enrichment using the text fragments provided by the data extraction function.

The list of links returned by the ResearchWebPage () function is passed to the dataExtraction () function which returns usable results (according to the coded ontology) that can be inserted into a database after validation by an expert. The latter, depending on its expertise, takes into account the categorization of the plant, the disease to be treated, the quality of the treatment to be administered and its effectiveness. It is this set of constraints that make it possible to present solutions with different degrees of relevance to a potential farmer in search of a solution to a disease linked

TABLE V
ALGORITHM 2: SEARCH WEB PAGE

Function: ReseachWebPage(listConcept):	
links[]	*/*empty list that will receive the links to the pages*/*
For concept ∈ listConcept	
req ← concept	*/*Giving the concept to mapping module */*
link ← getUrl(req)	*/*We extract the links from the previous page*/*
links[] ← link	
return(links).	

TABLE VI
ALGORITHM 3: DATA EXTRACTION FROM LINKS

Function: dataExtraction(links):	
For link ∈ links:	
page ← open(link)	*/*Make the query on the link*/*
content ← parser(page)	*/*Select the content of the page by eliminating tags and formatting.*/*
write(content, file)	*/* Write the content of the page to a file */*
return(file).	

TABLE VII
ALGORITHM 4: ONTOLOGY ENRICHMENT

Function: enrichiOnto(file):	
load(onto)	*/*Loading the ontology */*
For ligne ∈ file:	
Wordlist ← convertStrgWord(ligne)	
For word ∈ wordlist:	
If word ∉ C ∪ synset(c_i∈C) **Then**	*/*C is the signature of ontology.*/*
add(word, C)	*/*Add the word to the set of ontology concepts*/*
Else If word ∈synset(c_i∈C) **Then**	
add(word, C, equivalent)	*/*adds the word to the signature as the equivalent of an ontology concept. */*
return(onto).	

to his crops.

This knowledge base building approach can easily be extended to other areas of knowledge [34] such as using ontological modules and the Web to build a knowledge base in a chosen domain.

C. Remote Communication Agent results

A multitude of gateways exist for the implementation of the communication module between the ”SMSC” of the operator and the customer, some of which are owners (Alligate, Jataayu SMS Gateway, etc.) and others free like (Kannel , Gammu, etc.). The multitude of communication protocols with SMSC that ”Kannel” takes into account, as well as its ability to act as an SMS server, not to mention the quality and stability of these services in general are some of the reasons that led us to this choice.

D. Main contribution of the work

The results produced in this work have many advantages. The system architecture is obtained by embedding a neural network with less training difficulties using transfer learning and MLP. We have used a knowledge database searching system for plant pathology that can be enriched. The proposed architecture is not only reusable but also easily maintainable, in the sense that it is possible to take care of new diseases without having to modify the source code as it is the case with the proposals mentioned in the literature [23]. Indeed, we have a diagnostic agent for a set of diseases. In addition, the same system can be used to solve other problems in agriculture such as controlling temperature, humidity, soil PH, etc. by using the correct database of weights obtained through training.

VII. CONCLUSION

A real-time diagnostic system has been presented. The system is modeled as a collection of Agents which collaborate to perform decentralized monitoring an treatment of plants diseases. Three major functions are performed, monitoring and diagnostic, treatment process and communication with the farmer. The monitoring and diagnostic agent is implemented using neural network and the Prescribing agent is implemented using ontologies and a system of context-sensitive textual data extraction as proposed in [34]. The pre-trained ResNet101 and ResNet152 network architectures allowed us to extract features and MLP facilitated the classification. We obtain a final improved accuracies of 97.94%.

The current system is the result of an on-going research which was specifically commissioned to design and implement a modern solution for a remote monitoring and control in precision agriculture. The advantage of our approach is that, it’s possible to configure our diagnostic sub-system with different weights to solve a different problem like to monitor air temperature, humidity, ambient light, soil moisture and temperature. In our future work, it will be a question of integrating in this architecture the support of the control of the treatment process, which will have to automatically open a valve controlling the reservoir which contains the compound mixture for the treatment.

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