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Deep neural networks with transfer learning in millet crop images

Solemane Coulibaly[a,b], Bernard Kamsu-Foguem[a,*], Dantouma Kamissoko[b], Daouda Traore[b]

[a] LGP-ENIT-INPT, Université de Toulouse, 47 Avenue Azereix, BP 1629, 65016 Tarbes, France
[b] Université de Ségou, Ségou – sise à Sebougou. BP: 24, Ségou, Mali

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ABSTRACT

Plant or crop diseases are important items in the reduction of quality and quantity in agriculture. Therefore, the detection and diagnosis of these diseases are very necessary. The appropriate classification with small datasets in Deep Learning is a major scientific challenge. Furthermore, it is difficult and expensive to generate labeled data manually according to certain selection criteria. The approaches using transfer learning aims to resolve this problem by recognizing and applying knowledge and abilities learned in previous tasks to novel tasks (in new domains).

In this paper, we propose an approach using transfer learning with feature extraction to build an identification system of mildew disease in pearl millet. The deep learning facilitates a practically fast and interesting data analysis in precision agriculture. The expected advantage of the proposal is to provide support to stakeholders (researchers and farmers) through the information and knowledge generated by the reasoning process. The experimental result gives an encouraging performance that is the accuracy of 95.00%, the precision of 90.50%, the recall of 94.50% and the f1 score of 91.75%.

1. Introduction

Pearl millet is one the most important food crop in Mali and tropical. Millet diseases are important items in the reduction of quality and quantity in crop millet. Therefore, the detection and diagnosis of these diseases are very necessary. Traditional techniques of identification diseases require experts' knowledge of agricultural areas. Use these approaches to improve detection disease are difficult and less efficiently. However, the computer vision and the Internet of Things offer a new way disease crop detection based automatic pattern recognition. In fact, they contribute together about the development of agriculture. Thus we need to develop tools and methods to analyze, interpret and visualize the data in order to achieve significant results (e.g. meaningful outcomes in the detection of patterns in images). These systems will permit to generate knowledge support to help the farmers in the decision making process through execution of decision support systems [1].

Deep Learning is a set of automatic learning methods designed on the basis on "artificial neural networks" with multi layers. These networks are able to categorize information from simplest to the most complex, since there are relevant for supervised learning, unsupervised learning, and reinforcement learning [2]. Recently, several applications of deep learning have found solutions to many problems in image recognition and achieves the best results in many research fields, such as automatic plant disease, medical diagnosis and natural language. The main motivation of this work is to construct a deep convolutional neural network model to build an identification system for the disease mildew in crop millet.

The proposed approach applies transfer learning technique to make up for missing data includes three main steps: (i) image acquisition (ii) definition of a training network composed by "pre trained model" and "feature extraction" and (iii) disease classification. The pre training network is based on VGG16 model with ImageNet as source dataset. We have a small dataset of 124 images of diseased and healthy millet to identify mildew or no. At the end, we obtain the expected results: (i) the learning model from unlabeled image is constructed, the own network was used to learn in a new image (ii) the proposal method used for feature extraction to identify disease or not in input image.

This paper is structured as follows: the related works are presented in Section 2. Section 3 describes the methodology adopted. In Section 4, the detailed experimental context is presented and the last section (Section 5) concludes the work and presents the feature research.

* Corresponding author.
E-mail address: bernard.kamsu-foguem@enit.fr (B. Kamsu-Foguem).

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2. Related works

Images analysis is an important research area in the agricultural domain and it covers several problems: image recognition, image classification, anomaly detection, etc. [3,4,5].

Cheng, et al., have developed a convolutional network combined with residual neural networks to identify agricultural pests that have been threats to crop growth and storage of agricultural products [6]. An input to the network, an image's pest activates the first convolutional layer and the pooling system, and thus permits separating the pest from the rest of the image. Ten categories of pests have been identified. Grinblat, et al., proposes the use of CNN for the problem of identifying vein morphological vein of plants [7]. CNN has been used to train a set of plant vein patterns to identify others of a similar nature.

Rice is one of the most important food crops in the world. Rice diseases have a devastating effect on its production, and also it is a big threat to food security. Lu and its colleagues [8] have identified rice diseases using CNN. The study has categorized 10 classes of rice diseases on 500 images of infected rice and stems. The experience has shown that the CNN gives a better result than to traditional techniques of identifying diseases on rice, by using pattern recognition bases and machine learning.

Shiqi Yu et al., proposes a CNN model capable to classify a hyper spectral image, a good practice in precision agriculture, environmental monitoring and so on [3]. The CNN network is trained on the sets of labeled images (building, hill, pasture, etc.) and compared to labeled images with 81.75% of accuracy than traditional methods such as k nearest neighbors (KNN) and support vector machine (SVM).

Amara et al. propose a deep learning based approach that automates the process of classifying banana leaf diseases [9]. The authors use LeNet architecture as a deep convolutional neural network to classify banana sigatoka and speckle. They obtain 98.61% of accuracy with color images and 94.44% for gray images.

Another approach represented by Ramcharan et al., evaluates the applicability of the transfer learning from a deep convolutional neural network model for the cassava image datasets [10]. The model has identified three diseases and two types of pest damage: 98% for brown leaf spot (BLS), 96% for red mite damage (RMD), 95% for green mite damage (GMD), 98% for cassava brown streak disease (CBSD), and 96% for cassava mosaic disease (CMD).

Rangarajan et al. was used two pre trained deep learning models, AlexNet and VGG16 to classifying 6 different diseases and a healthy class of the tomato crop from the image dataset [11]. The classification accuracy has been 99.24% for VGG16 and 96.51% for AlexNet.

In summary, the deep learning applications deliver many opportunities in the field agriculture [12]:

1 Agriculture information processing: Monitoring the status of plants and animals is vital to agriculture production;
2 Agriculture production system optimal control: Control strate gies in agriculture production systems often rely on farmer experience or expert knowledge, which does not consider plant (animal) physiological status or real time demand;
3 Smart agriculture machinery equipment: Agriculture produc tion involves numerous kinds of tasks;
4 Agricultural economic system management: Agriculture yield itself is not enough for agriculture. There are many more factors should be considered such as the prices and the quality of agriculture products. It is very meaningful to predict agriculture product prices.

3. Proposed methodology

The proposed methodology uses the feature extraction that is an approach of transfer learning. It is based on the CNN model VGG16 that is pre trained on ImageNet. This section gives an overview of proposed method.

3.1. VGG16 overview

The VGG16 is proposed by [13]. It is a simple and widely used architecture for ImageNet. It takes as input an image of 224×224px and returns a vector of size 1 000 with the probabilities of belonging to each class. VGG16 contains 13 convolution layers, 3 fully connected layers and 5 pooling layers (as showed Fig. 1). The 16 convolutional layers are used to extract features from the ImageNet image. At each convolution layer we have a multiple filter of 3×3, with 1px as a stride. The last layer softmax is used for classification. In each convolution layer, ReLU is applied as an activation function.

3.2. Transfer learning

The algorithms of deep learning require a large dataset and a long time to training the different weights and the millions of parameters of deep network. This permits to have precision in

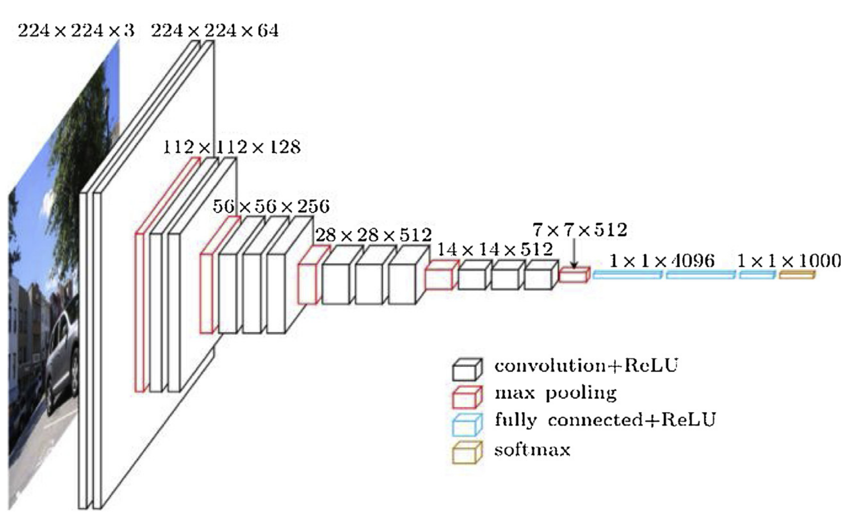

Fig. 1. VGG16 architecture [14].

knowledge representation. Firstly, the data augmentation method is a mean to enlarge the datasets. It uses the image transformation to avoid overfitting. Secondly, the Graphical Processing Unit (GPU) allowed to have computing resources to train a deep network. Also, the similarity (same feature, and same distribution) of training and testing dataset is necessary. In really, it's difficult and expensive to join these factors. At the same time, there are a gap public datasets in agriculture areas. The researchers develop their own system and that requires a long time of work.

One of the solutions that reduces effort at this stage is to utilize transfer learning, which provides guaranteed solution for an accurate classification with less training samples [15]. The transfer learning an Artificial Intelligence (AI) method to transfer knowledge from a related domain. Transfer learning is defined as the ability of a system to recognize and apply knowledge and skills learned in previous tasks to novel tasks and new domains [16] which share some commonalities (as showed in Fig. 2).

Transfer learning approach is particularly important in Deep Convolutional Neural Networks context for classification and noise reduction using several deep architectures trained [17]. With transfer learning, deep neural networks can learn very complicated relationships leading to overfitting (i.e. learned models having more parameters than necessary) and there exist some methods for reducing it such as regularization and dropout [18].

There is an obvious possibility for using the augmentation techniques of the training dataset if it is really too small. It is a matter of creating some variations of the same image by subtle mathematical transformations (e.g. rotation or translation) on the geometric shape. This is useful to avoid overfitting and increase the predictive capacity of the neural networks. There are two approaches can be used in transfer learning [15,19]: fine tuning and feature extraction. These both items depend of target dataset size and its similarity with the source dataset:

- Feature extraction: it consists of using the features of a pre trained network to represent the images from new datasets. These features are used to train a new classifier. Feature extraction makes sense if we have a large number of variables involved in complex data. Fine tuning is recommended in shallow part.
- Fine tuning: the fine tuning of the pre trained network is relevant when the target dataset is very large. It consists to unfreezing a few of top layer of a frozen model based used for feature extraction. Moreover, the parameters of all the layers (except the last one) are initialized those of the pre trained network, the training will be done more quickly than if the initialization had been random.

3.3. System overview

The Fig. 3. show the overview of the disease detection system of crop. It contains five components described as follows:

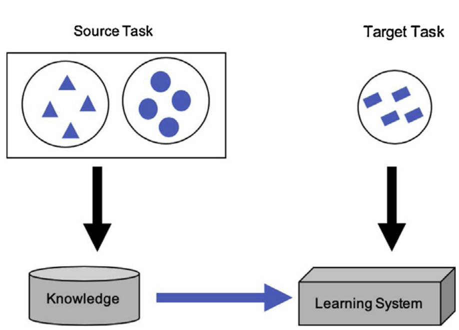

Fig. 2. Transfer learning [16].

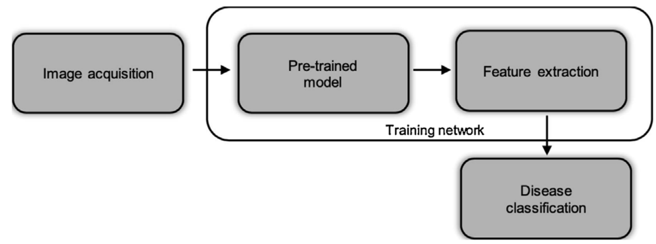

Fig. 3. Overview of the proposed transfer learning methodology/Approch/Flow chart of crop disease identification.

(i) Image acquisition: we must create your labeled datasets (source datasets) which will be analyzed. Our labeled dataset contains the images downloaded from the internet or captured from digital devices. The data sources are represented into different classes of images. Some images carry in them fungal attacks sent to the Training Network.
(ii) Definition of a CNN Training (Training Network): a training network was composed by "Pre trained model" and "Feature extraction." A pre trained is a save model that was already trained on large datasets such as ImageNet. This part was used to extract features for any image for the third component.
(iii) Disease classification: now we have a network has already learned. The last step determine which disease is present on input image: it's called classification input image. The output results represent the probabilities of class found. The detail of implemented system is presented in the next section.

3.4. Feature extraction approach

The implementation system in deep convolutional neural network is illustrated by Fig. 4. The CNN is trained with ImageNet as source datasets. ImageNet contains rather generic images and very few images on the mildew fungal attack. A pre trained network on this basis would not perform well for the disease identification problem on millet. Therefore, an adaptation is needed to modify the network provided. We propose a feature based architecture to offer a consistent adaptation. A deep learning model using a pre trained model like VGG16 is our basic architecture.

The proposed approach for feature extraction makes it possible to modify the classification of 1 000 classes of ImageNet to a classification of two classes consisting in determining as outputs the presence or the absence of mildew.

The new network is obtained by applying the following steps (as showed in Fig. 4):

(1) The first step initializes the network parameters for the second step. VGG16 is pre trained from the ImageNet, where it provides good performance in image recognition and classification. The last fully connected layers are removed, since it was used to classify the 1 000 classes of ImageNet.
(2) An adaptation is done in order to solve the new classification problem by freezing all weights of the pre trained layers.
(3) An extension is made on the model by adding two fully connected layers. The output of the fully connected back layer gives the classification for two classes: presence or absence of mildew. Thus, all the layers of the new model are trained on the new images (target dataset) and the final layer uses the sigmoid function to make the binary classification.

The experimental process is described in the next section.

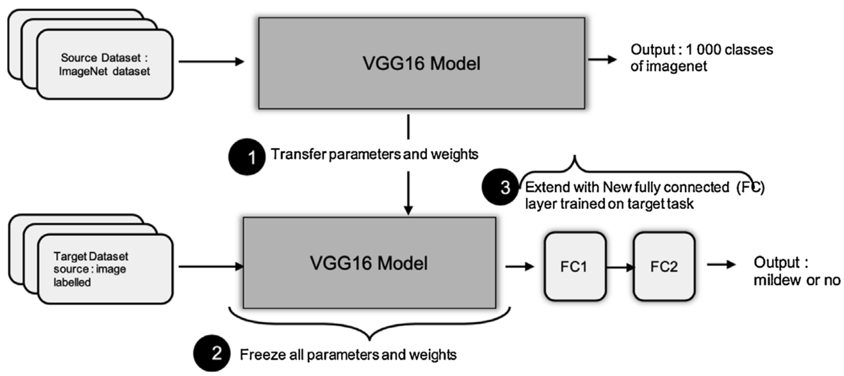

Fig. 4. Proposed approach for feature extraction.

4. Experiments

4.1. Source and target databases

There are many datasets for object recognition (ImageNet, Place, Caltech, etc.). For instance, we train a pre trained network on ImageNet, constituting of a many millions of images for generic object recognition for a few thousand classes.

The images of the target database were manually downloaded from internet and cropped each images to build the datasets. We have 124 images in our dataset. It's composed by different forms of mildew diseases and good health (as showed in Fig. 5).

4.2. Data augmentation/Datasets preparation

Data augmentation is an approach that generates more new data for existing data. Data augmentation is the creation (by rotation, flip, color variation, noise . . .) of transformed copies of each instance within a training dataset. It is needed to augment available data and increase the data size that it is fed to the classifiers in order to compensate for the cost required by additional data collection. We propose it in the training process through random transformations such flipping, zooming, shifting and rescaling.

For a given numerical value x, the following transformations are done:

- zoom: resizing of each image on the interval [1 x,1+x]
- rotation: each image is rotated on the interval [0, x]
- flip: the original image is transformed by a mirror reversal across a horizontal axis
- rescale: multiplication of the data by a specific value provided after the application of the other transformations.

Thus, we obtain a dataset composed of 711 images for training dataset.

4.3. Training details

Implementing a learning process can generate resource intensive and time consuming procedures depending of the quality of available data. Generally, 2/3 of data are used for training dataset and 1/3 of data are used for validation dataset. In the literature, the sharing of 80% and 20% as a basis for learning and validation is widely used.

In this work, the dataset was divided into a training dataset, a validation dataset, and a test dataset. The database also includes unseen images that form the basis of the test. The training and validation dataset contains 80% (99 images) of total images and the remaining 20% (25 images) are used for the test data.

We train 99 images tagged for training and validation datasets, including 70 images with mildew fungal pearl millet and 29 images without this disease.

We measure the performance of the model on several subdivisions of the base of the training and validation datasets. We have the following proposals: 80/20 (respectively 70/30, and 60/40) means 80% (respectively 70%, and 60%) of training dataset and 20% (respectively 30%, and 20%) of validation dataset.

The input image from RGB color of the network was resize in 150×150px to extract an important feature. The Stochastic Gradient Descent (SGD) with momentum is employed as an

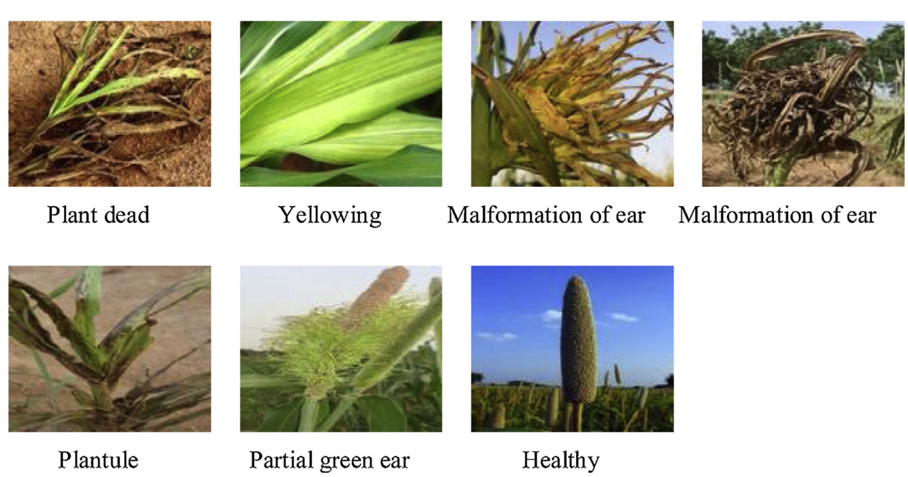

Fig. 5. Mildew images.

Table 1
Learning parameters.

Parameters	Values
Learning rate	1e-4
Momentum	0.9
Maximum iteration	100

optimizer. The optimization process is based on gradient descent which provides an iterative approach for minimizing a learning function. Over the iterations, corrections are made until the convergence. The gradient descent stops learning as soon as validation loss has stopped decreasing. The weights of the network become stable and the latter will converge to a value correspond ing to an overall minimum for the learning model. The local minimum is estimated at each epoch on the dataset validation. The Table 1 gives the initial learning parameters in the training step.

4.4. Experimental results

For the experiment, we use a deep learning framework widely known and accessible called Keras/TensorFlow [20] on a laptop Intel Core i5 with 2,7 GHz and 8 Go of memory.

A better performance of the model on the evaluation measures was obtained by the 80/20 configuration that was used for the test. The results are showed in Table 2.

The Early stopping technique is used to avoid overfitting and help to find this convergence value for the lowest possible validation loss. In practice this takes place through the patience defining the maximum number of (consecutive) epochs with no improvement on the validation set that is tolerated before the training is stopped. This value is obtained from the 30th epoch with a smaller loss validation of 19%. The test dataset used for the evaluation of the model includes 18 images with diseases and 9 without diseases. At the end of the 30th epoch, we obtain 95.00% accuracy on the validation dataset and 89.00% accuracy on the test dataset. The accuracy of classification with VGG16 as showed in the Fig. 6.

5. Conclusion and future research

The agricultural sector has undergone many changes in recent years. It has moved to the era of smart farming where the various steps of agricultural production produce data that can be processed and analyzed. A learning model and a decision support system are developed to better manage parcels and extract added value. Thus, the yields of plantations are significantly improved. Moreover, the disease identification is crucial to preserve this yield. In fact, we show the effectiveness of transfer learning for disease classifica tion with small data. The proposed approach identifies a mildew disease in crop millet. An approach based on feature extraction of a pre trained based on ImageNet. The performance of transfer learning gives 95.00% accuracy.

In the future, our goal is the detection mildew disease in tropical and in diverse crops (cottons, potatoes, etc.). Our solution can be integrated in digital camera or smart phones [21] for helping farmers to identifying plant diseases. One other goal is the selected disease area of crops using the segmentation case in deep learning.

Table 2
Accuracy result of experimentation.

Configuration	Accuracy	FMeasure	Precision	Recall	F1-score
80-20	**95.00%**	**91.67**	**94.50**	**90.50**	**91.75**
70-30	93.50%	88.66	91.00	87.50	88.66
60-40	94.00%	89.67	93.00	88.00	89.67

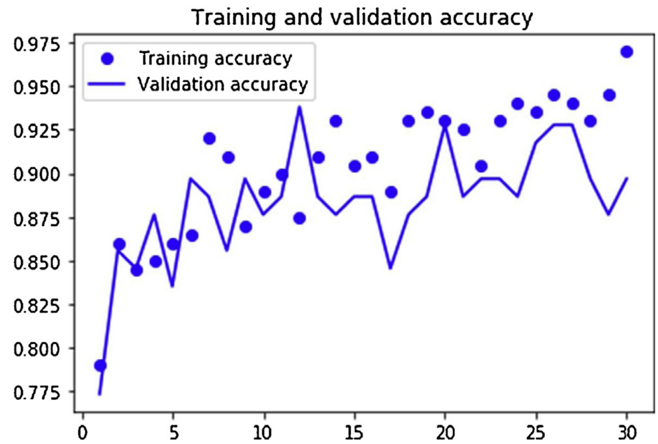

Fig. 6. Training and validation accuracy.

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Solemane Coulibaly has his Master in Computer Science of Sidi bel abbès's University of Algeria in 2011. He was a Web developer at CFAO Technology Mali from 2012 to 2013. Since 2013, he is an assistant professor at Segou's University of Mali. Currently, he is a PhD student of Doctoral School Aeronautics and Astronautics (ED AA) of the Toulouse National Polytechnic Institute (INP). He's taking research in the Production Engineering Laboratory (LGP) of National Engineering School of Tarbes (ENIT). His research includes Data Mining and Deep Learning techniques and performing interdisciplinary research relating machine learning, agriculture.

Bernard Kamsu Foguem is currently a tenured Associate Professor at the Toulouse National Polytechnic Institute (INP) and undertakes research in the Production Engineering Laboratory (LGP) of National Engineering School of Tarbes (ENIT). He was a visiting researcher at various foreign universities like in the United Kingdom (e.g. Oxford) and Finland (e.g. Helsinki). He got the "accreditation to supervise research", abbreviated HDR from University of Toulouse in 2013. He has a PhD in Computer Science and Automation (2004) from the University of Montpellier 2. His current interests are in Data Sciences (Data Mining and Deep Learning) and Knowledge Engineering (Semantic Analysis and Argumentation). The application range is extensive and includes industries and services (transport, energy, health and environment). He is a member of the editorial board of several journals: he is a member of Editorial Team of Artificial Intelligence Research (AIR) and Associate Editor for BMC Medical Informatics and Decision Making. He is a member of IFAC TC1.2 Adaptive & Learning Systems and co-facilitator of GDR WG Knowledge Engineering and Learning for Production Systems.

Mr Dantouma Kamissoko is Lecturer with authority to direct research since 2003 at the Université de Bretagne Occidentale (UBO) held the following positions: 1991-1995 head of department and research at the National School of Engineers of Bamako(ENI-ABT); 1997-2001 President of the PhD Students of the West of France ; since 2001 teaching researcher at UBO, ENI-ABT and University of Ségou (US); 2011-2013 Vice-Dean of the Faculty of Agronomy and Animal Medicine of the US, since 2013 General Director of the Institut Universitaire de Formation Professionnelle (IUFP) of US. My thesis under the direction of the Professor Paul Baird was made in the field of differential geometry and analytical geometry at UBO, after having Mr. Kamissoko validated 3 masters: CAAE (UBO), Econometrics (Université d'Orléans), Mathematics and Applications (Universités Orléans and Tours Rabelais). My research areas are: differential geometry, analytical geometry, convex optimization (Mathematics and applications) and applied statistics.

Daouda Traore is currently an Assistant Professor at the University of Segou and Deputy General Director at Institut Universitaire de Formation Professionnelle (IUFP). He has his PhD in Computer Science from the Grenoble Institute of Technology (Grenoble INP) in 2008. He was a Computer Expert Engineer at the National Institute for Research in Computer Science and Automation (INRIA) from 2009 to 2010. He was an Expert Engineer Development and Research at Sysfera society from 2010 to 2012. Since 2012, he works at the University of Segou. From 2014 to 2017 he was the Chief of the Department of Studies and Research at the University of Segou. His current interests are in Parallel Computing (adaptive parallel algorithms and their scheduling in the context of interactive applications, on multi-processor system on chips (MPSoCs)).