

Image Recognition Applied to Security Systems : The Case of Burkina Faso

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Abstract
In this article we propose à model composed of five layers of convolution and two layers of maxpooling and three layers of fully connected. What will allow image recognition to be applied to security systems: the case of Burkina Faso
The main contributions are :

- The establishment of a rapid and efficient aerial reconnaissance system ;
- Stable and fluid navigation of drones by learning the identification of simulated targets
- Improving security in Burkina Faso.

The results show us that the accuracy of learning and testing increases with the number of epochs, this reflects that at each epoch the model learns more information. If the precision is decreased then we will need more information to make our model learn and therefore we must increase the number of epochs and vice versa. Similarly, the learning and validation error decreases with the number of epochs.
Keywords : artificial intelligence, image, recognition, security, Burkina Faso
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1. INTRODUCTION

In the introduction to our article, the area we are working on and its importance will first be discussed; secondly the specific problem we are tackling will be discussed, thirdly the insufficiency of the existing state of the art will be justified and fourthly we will discuss our new approach to solving the problem, in fifthly we will say How we can evaluate the new approach, in sixth position the main contributions will be explicitly listed, and finally as a last resort the Roadmap for the rest of the document will be declined.

The field in which we work is artificial intelligence technology artificial intelligence apply to image recognition apply to security systems. Image recognition applied to security systems in Burkina Faso is the specific problem the article addresses. Burkina Faso is a low-income country in the Sahel with limited natural resources. Its economy is based on agriculture, although gold exports are growing. More than 40% of its population lives below the poverty line. The country is 144th out of 157 in the human capital index established by the World Bank.

The notion of "terrorism" saw its meaning evolve during the 19th century and target violence, perceived as "asymmetrical", committed by actors tending to destabilize a political or social order [1,2].

Attacks perpetrated by armed groups in Burkina Faso have increased since the beginning of 2016, and further worsened in the second half of 2019. From January to October 2019, more than 800 security incidents were reported, which resulted in several hundred deaths and injuries, so most of them were civilians. The deterioration of the security situation and the insufficient response of the Defense and Security Forces (FDS) throughout the national territory have caused a lot of internal displacement throughout the country. Inside the country, as in the border regions of Burkina with Mali and Niger, the failures of governance and the limited technological capacity of the State ensured security and the fight against organized crime are undermining its legitimacy and the very survival of the state. The artificial intelligence technology used to apply image recognition to security systems in Burkina Faso is important because it also allows data to be exploited at a level that no human could ever reach. Especially since in August 2022 the security situation is only deteriorating and we note more than 2 million internally displaced persons throughout.

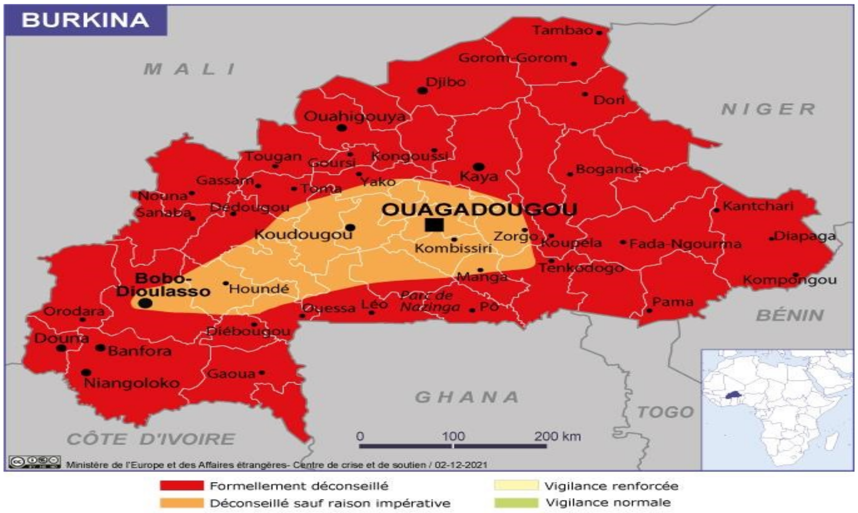


Figure 1 Burkina Faso security map 2021

The area in which we are working is important because it will save the 20 million inhabitants living in Burkina Faso who have been living with insecurity since 2016. This insecurity has caused several hundred deaths among the population as well as within the defense and security forces. The current country has only two priorities: the security issue and humanitarian action. Our work will contribute to achieving the objectives of securing the country. All of this will be done through artificial intelligence. Artificial intelligence improves business performance and productivity by automating processes or tasks that previously required human resources. It also makes it possible to exploit data at a level that no human could ever reach. In the field of public security, drones target "new" missions : surveillance of urban areas, highways, natural areas, forest fires, borders, or "new" areas : mapping, study of hurricanes, assessment of the consequences of natural disasters[3,4].

The difficulty and slowness of image recognition applied to security systems: the case of Burkina Faso is the specific problem attacked in our work.

The recognition of images remains such a delicate problem because the security systems do not have enough devices for recognizing and analyzing the images of criminals, which means that security difficulties in the country are increasing. These are marked by repeated terrorist attacks, the resurgence of organized crime and the appearance of self-defense groups that do not respect human rights in several localities of the country.

The rapid development of drone technology has greatly improved the degree of automation and intelligence making it the best choice for performing boring, difficult or dangerous tasks [5,6,7].

A new system for effective and fast aerial image recognition that will contribute to the manufacture of specific drones for the fight against insecurity is the new approach proposed to solve the problem.

To evaluate the new approach, we measure the speed and recognition efficiency of our system with existing systems.

The main contributions are :

- The establishment of a rapid and efficient aerial reconnaissance system ;
- Stable and fluid navigation of drones by learning the identification of simulated targets - Improving security in Burkina Faso.

For the roadmap for the rest of the document firstly related work will be discussed, secondly the new approach will be explained, thirdly we will describe the proposed model, fourthly the results and evaluation will be presented and discussion and future work will be the last part of the presentation of the work.

We have approached our field of work which is artificial intelligence applied to image recognition by presenting the security situation in Burkina Faso where the specific problem we wish to solve is the difficulties and slowness of image recognition by security systems. from this country. The new approach to solve the problem is to propose a methodology for the rapid aerial recognition of images which will contribute to the manufacture of specific drones. Thus the main contributions are the establishment of a rapid and efficient aerial reconnaissance system; system allowing stable and fluid navigation of drones by learning the identification of simulated targets and improving security in Burkina Faso. The following part of the article is transferred to related works.

2. RELATED WORK

In this section we talk about articles related to our work:

The Design and Application of the Airborne Realtime Image Recognition Computer System for Police

UAV,

The similarity of the article and ours emerges in three points: first we all work in the field of drones, then we approach the military field, and finally image recognition.

Over the past few decades, industry and academia have paid great attention to unmanned aerial vehicles (UAVs) due to their advantages of flexible mobility and low low cost [8]

The article talks about the drone system's close integration with the existing public security network, platform and investigation means, the existing platform and investigation means not only can avoid information islands, but also to participate in the high-level design as an essential element of information security, but also participate in the high-level design as an aerial reconnaissance element, thus contributing to building a flat command system integrating space and ground flat command system that integrates space and ground

Drone Deep Reinforcement Learning : A Review. This article is also similar to our article in the sense we are all working on drones.

The article observes that drones must have the ability to accomplish the planned missions in unexpected situations without requiring human intervention and to ensure this level of autonomy, many artificial intelligence algorithms have been designed. These algorithms targeted the following elements: guidance, navigation and control (GNC) of UAVs. The article also described the state of the art of a subset of these algorithms: deep reinforcement learning (DRL) techniques. The authors have made a detailed description, and we have deduced the current limits in this field. They noted that most of these reinforcement learning methods were designed to ensure stable and smooth drone navigation by learning computer-simulated environments. They then realized that additional research efforts are needed to address the challenges that limit their deployment in computer-simulated environments. The challenges that limit their deployment in real scenarios like in the situation in Burkina Faso.

In this section we have talked about two articles related to our article. In body of work We have brought out the similar points of these articles with our article. But what about our approach?

3. APPROACH

This article approach topic is the part where we give a high-level understanding of the new article contributions and the model pipeline overview.

The new contributions to our article are as follows:

- The establishment of a rapid and efficient aerial reconnaissance system;
- Stable and fluid navigation of drones by learning the identification of simulated targets
- Improving security in Burkina Faso.

The model we present is composed of:

- Five convolution layers
- Two layers of maxpooling
- Three layers of fully connected.

The contributions and the composition of the model clearly explains our approach which allows us to illustrate the description of our model in the following section.

4. MODEL DESCRIPTION

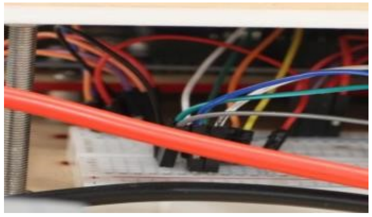
A présent nous présenterons les détails du fonctionnement de notre nouveau système c'est-àdire la description de notre modèle.

Nous proposons une model composé de cinq couches de convolution et deux couches de maxpooling et trois couches de fully connected.

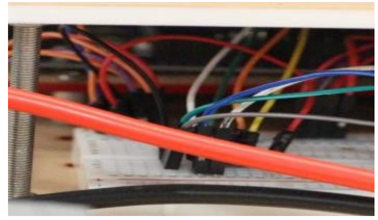
4.1. Data collection and organization

For the collect and organization we need to identify the images in order to collect them and then organize them. Thus the analysis of human activities, on the basis of video sequences, requires different levels of processing [9,10,11,12,13,14,15,16,17,18]. The human eye perceives an image as a set of signals that are processed by the visual cortex in the brain.

The result is a vivid experience of a scene, associated with concepts and objects stored in memory. Image recognition tries to mimic this process. The computer perceives an image as a raster or vector image. Raster images are a sequence of pixels with discrete numeric values for colors while vector images are a set of color annotated polygons[19,20,21,22,23]. After this stage of organization we must then classify the images. In our case we downloaded a dataset from the internet We have two large groups of TRAINING and TEST datasets; these 2 large groups are each subdivided into 2 parts: Mean and Real. Real represents the set of original images and Mean represents the set of noisy images.



Picture 2 circuit_11_mean



Picture 3 circuit_11_real

Picture 4 ball_7_mean

Picture 5 ball_7_real

4.2. Convolution layers

In recent years, convolutional neural networks (CNNs) have established themselves as a ubiquitous model in machine learning, achieving state-of-the-art performance in a wide range of tasks such as image classification [24,25,26,27]. The convolution layer is the key component of convolutional neural networks, and is always at least their first layer. Its purpose is to identify the presence of a set of features in the images received as input. Pooling is a commonly integrated feature in convolutional neural network (CNN) architectures. The main idea of a clustering layer is to accumulate features from maps generated by convolving a filter on an image. Formally, its function is to gradually reduce the spatial size of the representation to reduce the amount of parameters and computation in the network. The most common form of pooling is maximum pooling.

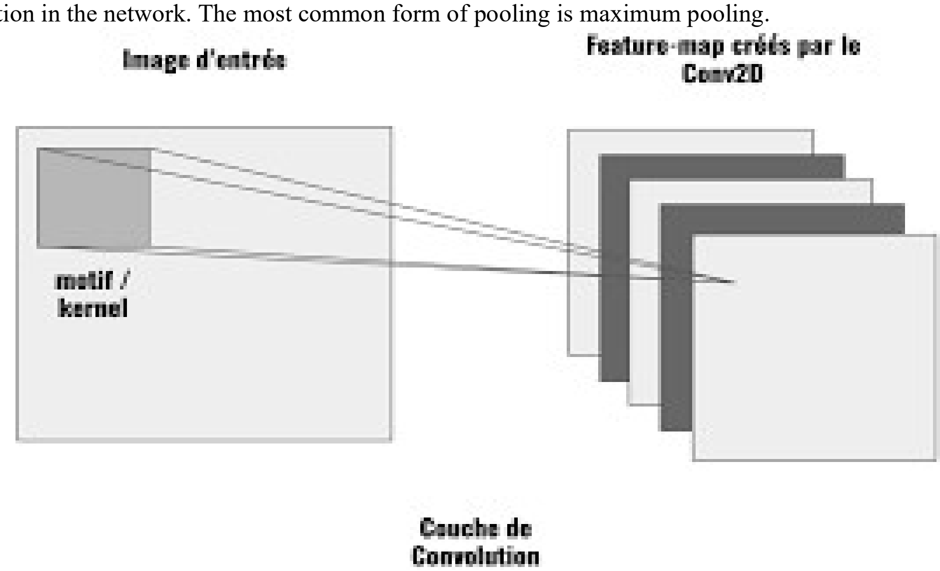


Figure 6 of a convolution layer

4.3. Max Pooling

Maximum pooling is done in part to aid overfitting by providing an abstract form of the representation. Additionally, it reduces the computational cost by reducing the number of parameters to learn and provides basic translation invariance to the internal representation. Maximum pooling is achieved by applying a max filter to the (usually) non-overlapping subregions of the initial representation. The other forms of pooling are: average, general. Max Pooling is a pooling operation that calculates the maximum patch value of a feature map and uses that to create an undersampled (pooled) feature map. It is usually used after a convolutional layer. It adds a small amount of translation invariance which means that translating the image by a small amount does not significantly

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affect the values of most grouped outputs.
The max-pooling operation in convolutional neural networks (CNNs) downsamples the feature maps of convolutional layers [28,29]

Max Pooling is a convolution process where the kernel extracts the maximum value from the area it convolves. Max Pooling is simply telling the convolutional neural network that we will only pass this information, if it is the greatest information available in terms of amplitude.

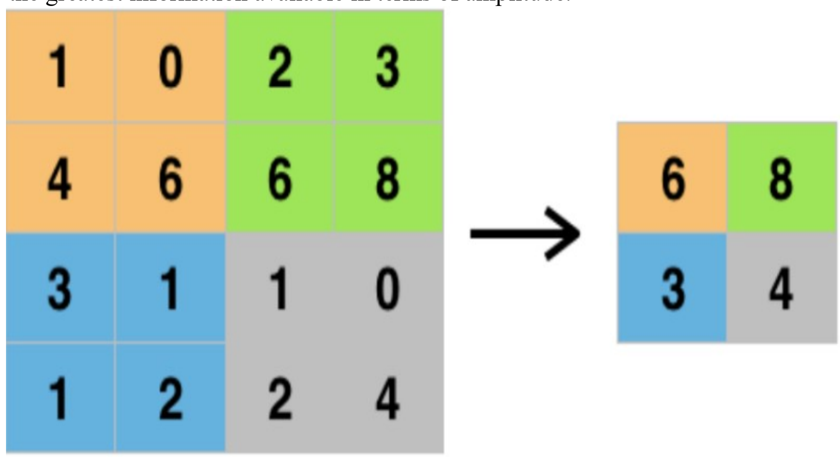


Figure 7 of a maxpooling layer

4.4. Fully connected

The fully-connected layer always constitutes the last layer of a neural network, convolutional or not – it is therefore not characteristic of a convolutional neural network.

This type of layer receives a vector as input and produces a new vector as output. For this, it applies a linear combination then possibly an activation function to the values received as input. The last fully-connected layer classifies the input image of the network: it returns a vector of size NN, where NN is the number of classes in our image classification problem. Each element of the vector indicates the probability for the input image to belong to a class. the fully-connected self-attention layer surprisingly lacks a specific dropout method [30,31]

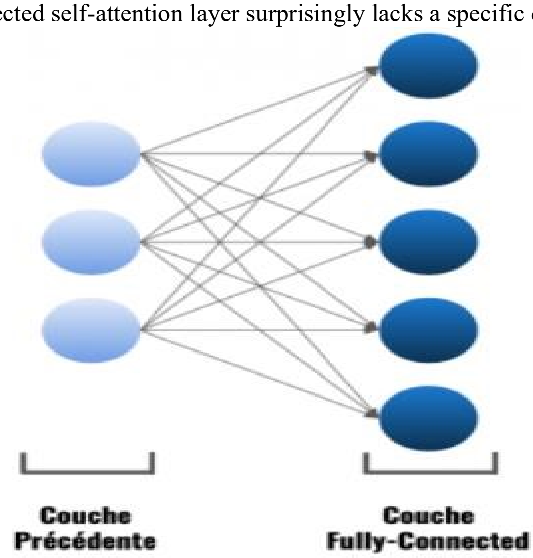


Figure 8 of a fully-connected layer

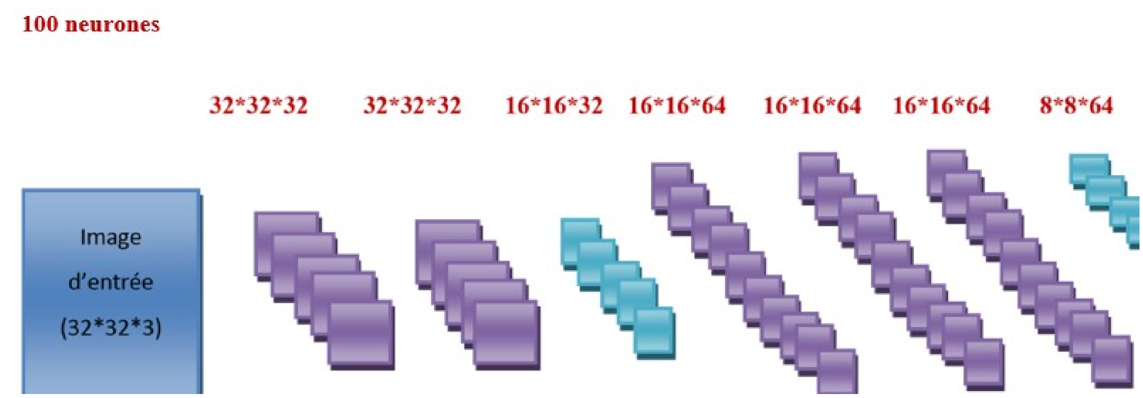
The input image is of size 32*32, the image goes first to the first convolution layer. This layer is composed of 32 filters of size 3*3, Each of our convolution layers is followed by a ReLU activation function this function forces the neurons to return positive values, after this convolution 32 feature maps of size 32* 32 will be created.

4.5. Model Architecture

The 32 feature maps that are obtained before they are given as input to the second convolution layer which is also composed of 32 filters, a RELU activation function is applied to the convolution layer, then Maxpooling is applied to reduce the size of the image as well the amount of parameters and calculation. At the output of this layer, we will have 32 feature maps of size 16*16.

We repeat the same thing with convolution layers three, four and five, these layers are composed of 64 filters, the ReLU activation function is always applied on each convolution. A Maxpooling layer is applied after convolution layer five. At the output of this layer, we will have 64 feature maps of size 8*8. The feature vector resulting from the convolutions has a dimension of 4096.

After these five layers of convolution, we use a neural network composed of three fully connected layers. The first two layers each have 1,024 neurons where the activation function used is the ReLU, and the third layer is a softmax which makes it possible to calculate the probability distribution of the 100 classes (number of classes in the CIFAR100 image base).



Model architecture
Figure 9

We presented in this description section of the model its composition which is five layers of convolution and two layers of maxpooling and three layers of fully connected, then we explained the operation of our model as well as the definition and functionality of the different layers and finally presented the architecture of our model. When are the results and evaluation.

5. RESULTS/ASSESSMENT

After presenting our approach, the description of the model, the results and evaluations of the implementation of the model are presented here with the errors and the precisions according to the epoche.

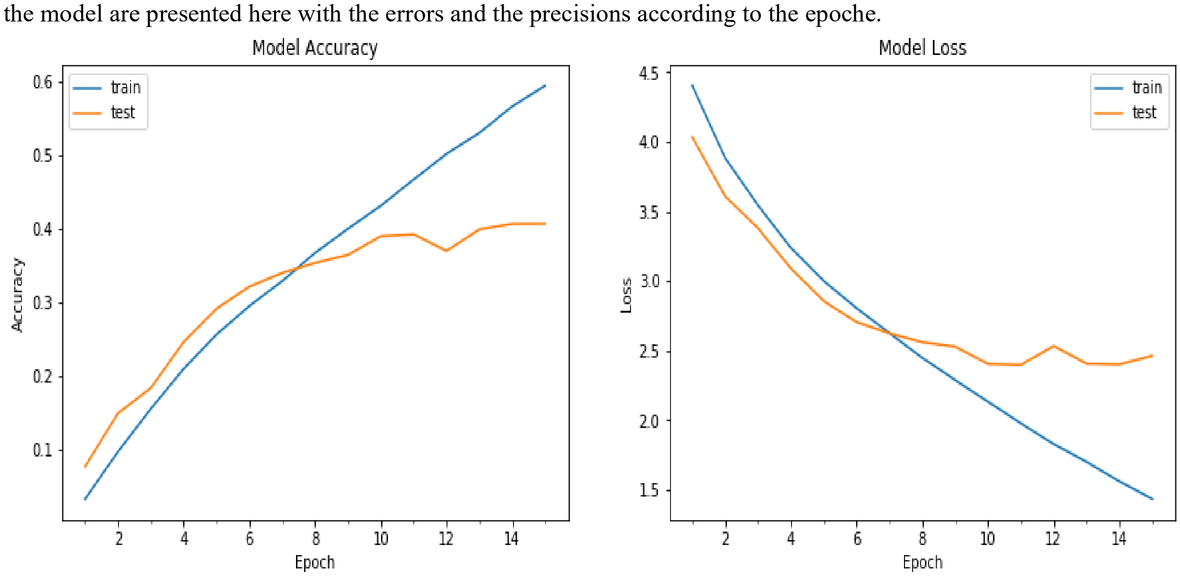


Figure 10 Accuracy and Error for the Model

The results show us that the accuracy of learning and testing increases with the number of epochs, this reflects that at each epoch the model learns more information. If the precision is decreased then we will need more information to make our model learn and therefore we must increase the number of epochs and vice versa.

Similarly, the learning and validation error decreases with the number of epochs.

We also notice that the total of misclassified images is 7977 images, an error rate of 79.77% and the total of well classified images is 2023 an accuracy rate of 20.23%.

We presented the results which show that our model is a leading model among the various existing models. And to say that our model adapts while learning, the more the number of epochs increases, the more the precision is clear, which makes the originality of our model.

After the results and the evaluation, we will move on to the discussion and future work.

6. DISCUSSION AND FUTURE WORK

At the end of our work, our main contributions are listed as follows: The establishment of a rapid and efficient aerial reconnaissance system; Stable and fluid navigation of drones by learning the identification of simulated targets; Improving security in Burkina Faso.

With the model we propose, the precision of learning and testing increases with the number of epochs, this reflects that at each epoch the model learns more information. If the precision is decreased then we will need more information to make our model learn and therefore we must increase the number of epochs and vice versa. Similarly, the error of learning and validation decreases with the number of epochs.

If we were able to render photo-realistic images using a model learned from data, we could turn the graphics rendering process into a problem of model learning and inference [32,33,34,35,36,37,38]. In general, a large and deep convolutional neural network gives good results and the performance of our network degrades if a convolutional layer is removed. For example, according to the table Eliminating one of the two middle layers causes a loss of about 5% in network performance. Therefore, depth is essential to achieve good results.

The results obtained improved as we deepened our network and increased the number of epochs. The learning base is also a determining element in convolutional neural networks, it is necessary to have a large learning base to achieve the best results. The use of unmanned drones for aerial reconnaissance and evidence collection has the following characteristics: fast response, high real-time performance, and faithful and reliable images [39,40,41,42,43,44]. For future work it is desirable to apply our model to the use of drones for aerial image recognition.

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