An Intelligent System to Track Tree Loss in Rural Africa using Satellite Image Data

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ABSTRACT

Given the devastating effects of deforestation for the environment and local populations in rural areas of Africa, monitoring changes in vegetation coverage is an essential task of many development organizations and local forestry services. Currently, there are no systems or tools available that provide the necessary information for this context. In this paper a fully functional and user-evaluated system for remote monitoring of tree and vegetation coverage is presented. The system uses machine learning algorithms based on the ideas of convolutional neural networks and U-Net architecture. The system and its user interface have been designed, built and evaluated according to requirements of two local NGOs in West Africa.

KEYWORDS

deforestation, satellite imagery, remote sensing, image processing, vegetation monitoring, ICT4D

1 INTRODUCTION

Tree theft and deforestation are a real problem many people face in rural drylands in West Africa. Trees are being stolen from private lands which can dramatically influence the lives of the rightful owners in very negative ways [8].

In the rural communities in the southern part of Mali, which is the region of focus of this paper, one of the most prevailing biome are the savannas. Trees have significant influence on the closest surroundings, influencing both the local fauna and flora [40]. Changes in forests and tree cover can greatly affect the ecosystem in terms of climate regulation, biodiversity richness, water supplies and carbon storage [15]. The illegal tree cutting is a big obstacle in any regreening efforts of the drylands, which promise to transform the degraded landscapes into productive areas with sustainable land management practices [35].

Trees are disappearing from privately held properties of the local people because of tree theft conducted by small organised groups. For the local forestry services it is difficult to fight this crime because of the large ground area needed to be covered.

Remote sensing and in particular satellite images analysis is a promising complementary tool to help the authorities fight these crimes, track deforestation and regreening. The public and private imagery from satellites provides high resolution view of the Earth on a periodical basis. Remote sensing can be done utilizing data from different kinds either airborne or spaceborne sensors. Furthermore powerful signal processing methods are being developed which allow exploiting this information even in greater detail [5].

The combination of the vast amount of satellite data with modern data processing techniques, including machine learning, has the potential of bringing tremendous value to help to identify tree theft in West African countries.

The goal of this research was rooted in the formulated research question:
Can we design a system or tool that can help monitoring the tree loss and changes in tree coverage in rural Africa?
And additionally, two sub-research questions to be addressed in order to develop the potential system:

(1) Sub-RQ1: What is a suitable AI-based remote sensing approach to monitor changes in vegetation coverage and individual trees?
(2) Sub-RQ2: How should the user interface look like, to make the system usable for its targeted users?

In this research, I have analyzed, designed and developed a sustainable tree cover analysis remote sensing system, that can automatically analyze large areas of land using artificial intelligence algorithms, and provide insights on the tree cover. This system is developed for the context of rural Africa and therefore, there are constraints and requirements related to this precondition.

The project should be understood as a first step towards achieving that overarching goal of identifying illegal tree-cutting. This research strives to design and implement a tree monitoring system, excluding the temporal dimension of analysis, thus no comparison between different satellite images will be implemented at this point.

In the upcoming section, I will describe the background for this project, this touches on ICT4D project specifics and stakeholders. In section 3 the insights into remote sensing and related work will be presented, with the direct contribution of this project. In section 4, the used methodology during the research will be covered. Section 5 walks through the actual conducted research and all of it's stages in detail. Section 6 discusses the sustainability aspects and future work. Finally in section 7 a conclusion of the work conducted in presented.

2 BACKGROUND

Big part of this research is designing and developing Information and Communication Technologies (ICT) solution for rural Africa. Because of the socio-economic impact for a developing country, it is understood as a project regarding Information and Communication Technologies For Development (ICT4D) as defined by [17]. Besides ICT4D context, this chapter introduces the stakeholders.

2.1 ICT4D context

When conducting ICT4D projects, sustainability is a very important aspect that has to be take into account. The economical, social and environmental impacts the proposed solution carries are fundamental in evaluating the projects as success or failure [31].

Development and implementations of a system for the use in the third world countries can raise many challenges that can be hard to predict. This can be entirely different cultural and social background [11], where many misunderstanding can happen regarding clarifying the goals of the project and setting requirements. Another challenge can be the different levels of education of the users and other stakeholders. In that context, the project should for example consider the appropriate interface to use the system and make it understandable from the point of view of the actual users [32].

Apart from the social aspects, there can be many regarding the context of implementation. In that terms it is important not to make assumptions around infrastructure like presence or stability of connection networks, hardware or even electrical energy [11]. Furthermore often the designed solutions are deployed in drastically different environmental conditions, like heat and dust. This could be problematic especially for hardware solutions.

In order to fulfil the expectations, it is important to adapt the applied methodology. Some of the common practices suggest communicating the progress of the project frequently and proceed in an iterative manner [6].

2.2 Stakeholders and project context

The system that is being researched and developed in this project has been requested by Mr. Amadou Tangara and Mr. Mathieu Ouedraogo. Mr. Tangara is a country manager for the non-governmental organization (NGO) in Mali. Mr. Ouedraogo is the president of Réseau MARP, which is a NGO in Burkina Faso. During the research, Ms. Anna Bon, who is the supervisor of this thesis, has facilitated the very important communication between me and Mr. Tangara and Mr. Ouedraogo.

Once the system is implemented, the direct users of the system will be organizations who support farmer-managed regreening in Africa. Some of the organizations that have already shown interest is the Dutch organization Both Ends (www.bothends.org) or Mr. Chris Reij from World Resources Institute in Washington DC, USA.

The mentioned stakeholders have expressed interest in monitoring and analyzing trees using remote sensing technologies. The ultimate goal would be tracking change of vegetation particularly in areas with high regreening or deforestation activities. Specifically the NGO in Mali is very interested in the use-case of tracking illegal tree cutting. The hopes are that a system could ultimately provide hard evidence to the local authorities to fight tree theft.

The reason for requesting such system by the stakeholders, is that at the point of the research, there are no remote sensing systems that would satisfy the needs of the stakeholders. The available tools are both very expensive and extensively complex to use. There is a tremendous need for a remote monitoring tool that is both user-friendly for this specific purpose, and at the same time can be operated at a reasonable cost.

This project tries to make a system that demonstrates the capabilities of satellite image analysis in this context and sets the ground for future research that would extend the introduced system.

Monitoring the vegetation is an important part of any project that aims to protect trees in rural areas which makes many governments, organizations and donors very interested.

3 STATE OF THE ART OF SATELLITE IMAGERY ANALYSIS

3.1 Remote sensing

In essence, remote sensing is the acquisition of some insights about the object or phenomena of interest, without having the measuring device in a direct contact with the subject [22].

Remote sensing sensors can be classified as either active or passive. Those sensors, which react to the natural radiation emitted or reflected from the observed surface (e.g. reflected from Earth) are called passive, an example would be digital camera. The active sensors produce their own electromagnetic radiation in order to illuminate the surface by this artificially created radiation. A digital camera with flash could be considered an example of an active sensor.

There are several major parameters which define the characteristics of the captured data. *Spatial resolution*, is a measure of the smallest object that can be resolved by the sensor. Usually expressed in meters or centimetres per pixel. *Spectral resolution*, the spectral bandwidth with which the image is taken, meaning the range of the captured wavelengths. *Temporal resolution*, denoting the time interval between individual observations of the same area of interest. *Radiometric intensity*, which is the number of discrete values of brightness the sensor is capable to distinguish. [29]

There are also 2 different categories of remote sensing systems from the perspective of where the sensors are: airborne systems and spaceborne systems.

Airborne systems, which include plains and unmanned aircraft systems (UAS) with attached sensors, operate on relatively low altitude above the Earth's surface. Being closer to the observed area allows for higher spatial resolution and use of sensors which can not operate from the spaceborne systems. One of such sensors is LiDAR, which can create a 3D map of the scanned surface and thus providing the height information about the examined objects. This method of remote sensing is useful only on local basis. In case of large areas or on the global scale using air-crafts becomes unpractical. [23]

Spaceborne systems offer much larger aerial coverage than airborne systems. It is mostly sensors attached to satellites or spacecrafts capturing the surface of the whole planet Earth. Some of the satellites are operated by governments which provide the captured data freely without charge. One of such satellites is the Sentinel-2 operated by the European Space Association (ESA) launched in 2015 as part of the European Copernicus program [19] which provides for multi-spectral imagery spatial resolution of 10 meters per pixel [26]. At the time of working on this paper, this is the best spatial resolution out of all the publicly available satellite imagery sources, right in front of the popular Landsat project of the USGS/NASA initiative with spatial resolution of 30m [21]. The 10 meter spectral resolution in unfortunately not sufficient for identifying individual trees. There are privately operated satellites which offer spatial resolution up to 0.35m [4], one of such providers is the company DigitalGlobe.

3.2 Satellite imagery analysis

What is important to note, especially in the case of analysing satellite imagery is how the satellite data is presented. Light can be either reflected from the object surface, it can be absorbed, scattered or refracted. Optical sensors measure the quantity of light reflected by the surface observed in a given range of wavelengths. If all of the wavelengths reflected from the surface are observed together, we speak of a panchromatic image (all colours are included), these are usually presented as grey-scale imagery [9]. In other cases, wavelengths can be divided into multiple bands, each of the bands having own wavelength range. This separation into multiple bands produces so called multi-spectral images [9]. An example of such band division is shown in Figure 1, where the bands are denoted as *Visible*, *Near Infrared* and *Middle infrared*. Various materials differ in reflectance of different wavelengths. It is possible to show how much of the electromagnetic radiance is reflected from that material across the wavelength spectrum, this is called spectral signature. For example vegetation has strong response to near infrared wavelengths and in this band can be easily differentiated from other types of materials like water [9]. Different materials can be identified by the reflectance intensity in different wavelength bands. It is even possible to distinguish between different types of vegetation like trees and grass from the spectral reflectance Figure 1. Characteristics of the material can be amplified by calculating various arithmetic combinations of bands called indexes to highlight certain features in the image. This feature is often used to classify what does each individual pixel in the image represent, like vegetation. One of indexes highlighting the reflectance of vegetation is the Normalized difference vegetation index (NDVI) [41] which is computed from near-infrared and red spectral bands as presented in formula 2.

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{nir}} - \rho_{\mathrm{red}}}{\rho_{\mathrm{nir}} + \rho_{\mathrm{red}}} \tag{1}$$

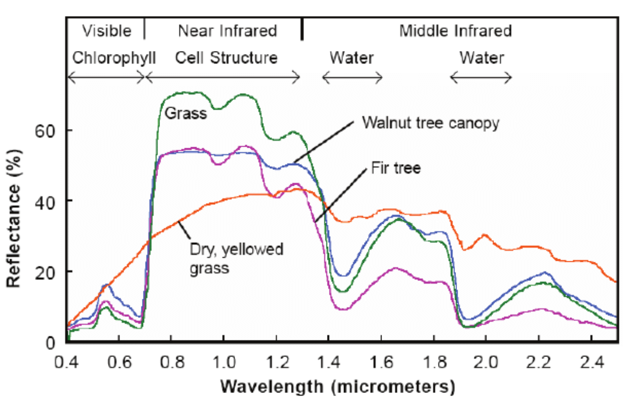


Figure 1: Reflectance spectra of different types of green vegetation (Smith, 2001a)

3.3 Related work

In the domain of vegetation analysis from satellite imagery, there have been multiple types of different applications developed. They can be categorized based on the unit of analysis they examine.

One category is identifying individual trees in the imagery. Various approaches have been developed on detecting individual trees from remote sensing data, however these methods usually require the combination of very high spatial resolution and often specialised sensors like LiDAR for height detection as an additional source of data. Methods used in these experiments, like edge detection and locating local maxima of the pixel values are only usable with very high resolution satellite or airborne imagery. The spatial resolution of the input images is usually 0.6m or better. The very high resolution is necessary because the shapes of the trees need to be clearly recognisable in order to conduct object detection. Often supervised learning algorithms are utilized and thus fairly large sets of training data are needed. In addition these applications often focus only on identifying trees of one species that can be easily detected and are constrained with a specific pattern in how the trees are planted (eg. grid planting structure on farms). The paper on counting of palm trees on plantations is an example of such restricted context application [4]. In order to identify individual trees, human aided systems are developed. The paper on identifying trees for wild-forest-fires simulations [7]. This paper describes an application that allows the user to guide the automatic detection of trees from satellite imagery and spatial vegetation data for the purpose of building virtual reconstructions of the world for wildfire simulations. The system relies heavily on the user, during the execution of the algorithm user has to take action and tune all of the important parameters by his/her own judgement in order to get the best result as a trial and error process. Because of that, the user has to be highly trained in order to use the system.

The other category of use cases takes a different approach than the object detection described earlier. The images are analyzed on a pixel basis instead of trying to identify whole trees, this method is called segmentation. By doing that an area is identified pixel by pixel where the material is categorised usually based on the spectral signature of that material. This approach is more suitable for lower resolution images like the one from Sentinel-2, Landsat and other public satellites. This way, applications on crop species classification and in the forestry domain on estimation of the forests gain/loss and tree species classification [19, 27].

3.4 Contribution

The contribution of this thesis is a fully functional monitoring, easy to use tool that can be easily used to analyze tree coverage in Mali, Africa at low cost. Moreover this project provides a much needed deeper insight into the specific context of using satellite imagery for tree segmentation and detection in the regions of Mali, Africa. These insights are encouraged to be used to build on this project and ultimately create a full-fledged, easy to use detection system which many government organizations, NGOs and others are in a desperate need for.

4 METHODOLOGY

In order to approach the research in a concise, appropriate manner for its context, I implemented a methodology, which is heavily inspired by the agile software development life-cycle [3] and the ICT4D methodology for similar projects [30]. This methodology consists of 5 consecutive phases as depicted in Figure 2.

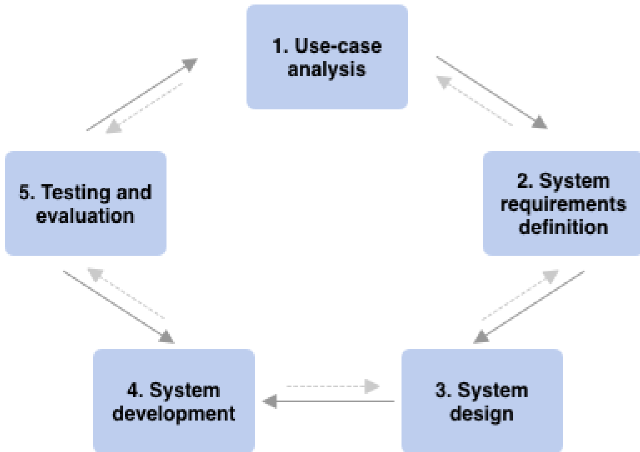


Figure 2: Iterative project life-cycle

ICT4D projects. That is because these projects usually have somewhat experimental nature. In the case of this project as well, many of the requirements are either unknown or vaguely specified. This is why the developing such systems has elements of experimentation and discovery and thus needs to be fast and cheap [6]. As stated by [13], agile development methods with iterative nature are very fitting for ICT4D projects. As mentioned, an important aspect of this methodology is the iterative character. In each iteration, the produced solution should be closer to the desired, at first vaguely formulated, outcome. In case of this research, in total 3 iterations have been conducted. Only the last 2 iterations will be described in detail, since the first iteration was dismissed early on into the research and was mostly about familiarizing with the topic and selecting data source.

Each iterations consists of 5 consecutive phases. However if needed, it is allowed to return to previous phase, as denoted by the small back arrows in Figure 2. This is useful if the newly discovered facts provide insights that point out to a change in previous believes.

In the **Use case analysis** the goal is to understand the different stakeholders, identify the problem and outline the goals and expectations they have from the system.

Phase **System requirements definition** is about formally defining the functional and non-functional requirements for the final solution. This should be done after a broader understanding of the stakeholders and use-cases is established. Their expectations, goals and use-cases has been captured in previous phase.

The following phase is the **System design** step. Because of the usually unfamiliar environment where the system will be deployed and used, numerous factors and constraints have to be taken into account when designing the system. Find out about the context and the constraints set by the context and make design decisions to address them. In an ICT4D project, this might be a little more challenging but is nonetheless important because of the unfamiliarity of the circumstances, needs and limitations of the users. One of the appropriate methods for conceptualizing the design and decision made, is Questions Operation Criteria modeling method (QOC) [25]. QOC is a method to visualize the design space and make better decisions. Each of the options supports or challenges a specific criteria which is a important requirement for the project. By visualizing the design space, where all options are presented, and all the affected criteria are assessed, an informed decision can be made on which option to pursue for the biggest benefit.

The second to last phase is **System development**, where architecture, data processing and the development of the system itself is discussed in detail, including all the rationale and implications for the specific choices.

In the last phase **Testing and evaluation**. A closer look is taken to assess the performance of the developed system, and relate it to the goals and expectations proposed earlier.

5 CASE STUDY

This section will cover the whole life-cycle of the development of the system for monitoring trees in Mali Africa using satellite imagery. The iterations conducted during the research project and their steps as introduced in the methodology section will be described. In total there were 3 iterations. The first iteration was a denied shortly after the start so it is considered as *Iteration 0*. This iteration was mostly about researching appropriate satellite imagery data sources and is briefly described in System design section (subsubsection 5.3.1) including the ramifications. Full detailed description is provided for the other 2 more relevant iterations for readability purposes.

5.1 Use-case analysis

The initial request was for a system, that could in any way, help with monitoring the vegetation in Mali Africa, in the Tominian region. The monitoring should focus on tracking illegal tree cutting of individual trees because they are vital for the environment in many ways as described in the introduction section. The problem the authorities are facing, is the lack of evidence through the absence of hard quantitative data, which makes fighting the tree cutting very difficult. It is infeasible, both from time and costs perspective, for the authorities to track the incidents only with human force, even more so, preventing the tree cutting from happening in general. For the local people it can be dangerous trying to stop the theft form happening or even simply reporting these organised groups responsible for the crimes. A cost effective system, that would provide quantitative data about tree cutting to the authorities, would help with solving this problem.

It became obvious, that building the full system, that monitors tree cutting is beyond the scope of this research project. After talking to the stakeholders, an alternative approach was established. In this research, the developed system should monitors trees and their count as requested, but should not do so on temporal basis. The comparison element between individual images will not be included at this moment. Also, the system should be designed in a way, that would allow other researches to easily continue with the work and extend this project towards the ultimate goal. This sets a realistic expectation on the system and makes it a very good starting point for any further extension, since in order to achieve the original request of comparing tree counts on timely basis, the system will be just extended. Additionally tracking the tree count and coverage will provide very valuable insights about the region as well and is thus set to be the new goal of the project.

The stakeholders and a more detailed context on their overall expectations is described in subsection 2.2.

Two important use-case scenarios have been set for the system. For the second iteration, the use-case analysis remained the same.

5.1.1 Tree cover analysis of a desired area in Tominian region on demand. The system needs to provide a user interface (UI) for a interested user to easily analyze any area in Mali in the Tominian region. The system should provide the analysis results in a reasonable time, ideally right in the same interface. The use-case should be easy to execute without any extensive training necessary.

This use-case was further specified in the feedback for the first iteration. In the next version there should be a support for French interface. As French is the official language in Mali, the system has to provide both English and French interface. It should also be possible to export the analysis results.

5.1.2 Automated continuous tree cover analysis of a desired area in Tominian region. The system has to be designed in a way, so it is possible for continuous automated analysis of the area of interest. This has to support the use-case, where a analysis is set-up and interested parties are informed if an abnormal situation is encountered. Support for such automation ensures adherence to the original request of developing a illegal-tree cutting monitoring service and possibility of and extension for such functionality in the future.

5.2 System requirements definition

From the conducted use-case analysis, it was apparent, that both functional and non-functional system requirements are vague and often open-ended. This is because the stakeholders are treating the project as an experiment to explore the possibilities and just give a direction to pursue. Based on the communication with the stakeholders through Ms. Bon, who mediated the communication with interested parties in Mali Africa, a list of requirements was put together. Both functional and non-functional requirements collected during all the iterations are presented in Table 1.

Functional Requirements	
Must Have	- Analyze satellite images for canopy cover. - Analyze satellite images for tree count. - Show map. - Show predictions map. - Show tree count analysis result. - Show canopy cover area size analysis result. - Present area analysis results in both meters squared and hectares. - After analysis show the coordinates of the AoI polygon. - Provide both French and English user interface.
Could Have	- Analyze specific regions by defining own area of interest (AoI). - User interface (UI) to intuitively define AoI for analysis. - Implement a feedback for into the web application.
Non-Functional Requirements	
Must Have	- It has to be possible to use the system without any special training. - For deploying and using the system, no dedicated hardware should be needed. - System has to have modular architecture in order to allow for further development and extension. - Systems architecture has to be prepared for future automation of analysis executions.
Could Have	- Running and operating the system shouldn't introduce extensive costs. - The results of the executed analysis presented in a timely manner. - In second version, try to improve the accuracy of canopy cover predictions.

Table 1: Functional and non-functional requirements

5.3 System design

There were several important design decisions that had to be made before, or right after starting with the system development. In order to make those decisions, and reason about the rationale, QOC analysis has been conducted [25]. QOC analysis has been performed for 3 important design questions as described in the sections below.

5.3.1 What satellite data to use? The choice of where to get the satellite images from was intensively researched at the start of this project. The QOC diagram Figure 3 visualizes the final decision made.

- **Q1-O1 Public satellite images:** Provide medium resolution imagery of the region of interest publicly free of charge. Images could be analysed more often.
- **Q1-O2 Private satellite images:** Imagery provided by privately operated satellites have very high spatial resolution but are expensive.

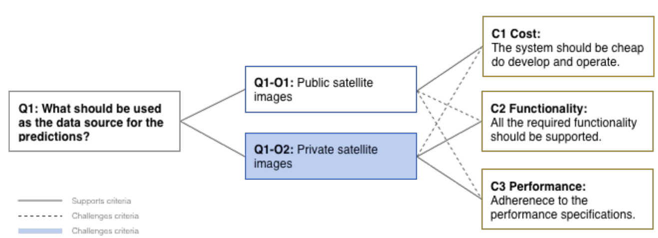


Figure 3: QOC diagram for prediction image source

Rationale for choice Q1-O2: The initial idea at the start of the research, was to explore the possibility of using public satellite images as data source opposed to images from privately operated satellites. This is because the public images are for free, which would allow to analyze the images on more frequent basis. This option was researched right at the start of the project, in what I call *Iteration 0*. Soon after exploring this option, it was obvious that for individual tree monitoring tool, the public satellite imagery doesn't offer high enough spatial resolution. To demonstrate this limitation, both Figure 4 and Figure 5 show the exact same location. As the goal is monitoring individual trees, from the figures it is obvious the 10 meter resolution of the public image does not offer the detail needed. The 10 meter resolution image is from the Sentinel project. Sentinel is a satellite program operated by the European Space Agency (ESA) and offers the highest resolution of any publicly available satellite imagery [12].

Because sustainability and cost is a big factor in this research project, extensive research has been conducted in order to find very-high resolution images that would be usable for desired detailed tree analysis. One satellite image of the desired Tominian area was found as a sample image from a commercial vendor of space imagery called Digital Globe. This image covers roughly 800 km^2, was dated 01/03/2017 and is captured by the WorldView-3 satellite and provides 8 spectral bands. Because March is the middle of the dry season, the image offers the needed spectral data and covers the area of interest (AoI), it was evaluated as well suited to be used in this research. Because the image can be used free of charge, it dramatically brings down the cost of the research.

Since the vegetation landscape undergoes radical transformation throughout the year [28], therefore analyzing trees in the wet season and the dry season is very different. A decision has been made, that analysis will be only conducted during the dry season, which will be the focus of this study. The reason behind this decision is that the grasslands and bushes that emerge during the wet season (as well as other seasonal vegetation) are not of the interest of the analysis and only introduces undesired noise. Dry season landscape exposes individual trees in much more prominent way.

Figure 4: Public Sentinel image spatial res. 10m

Figure 5: Proprietary Digital Globe image spatial res. 0.3m

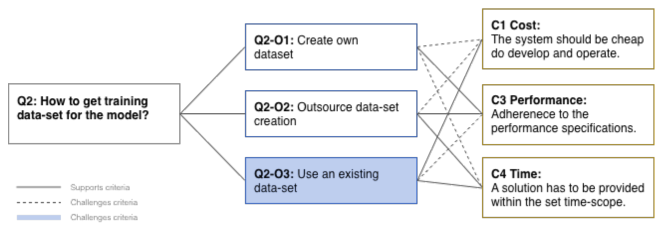


Figure 6: QOC diagram for getting data-set

5.3.2 How to get training data-set? In order to build accurate prediction model as intended in this research, the model needs to be trained on preferably very large labeled data-set. An example of a image, mask pair needed for training is shown in Figure 9. This data-set should well represent the predictions that are ultimately expected from the model. A training data-set for this use case (tree recognition in the regions of tropical savannas) was unfortunately not available. When considering how to get a relevant training data-set, 3 options were evaluated. The QOC diagram is presented in Figure 6.

- **Q2-O1 Manually create own data-set:** Manually label hundreds of images from the Tominian region to be used for training.
- **Q2-O2 Outsource custom data-set creation:** Outsource the custom training data-set creation, to a 3rd party.
- **Q2-O3 Use modified similar existing data-set:** Utilize existing training data-set, which was created for similar purpose with similar context.

Rationale for choice Q2-O3: Manually creating custom data-set would be very time-consuming and probably could not be completed within the time-scope of this research. In addition to that, the necessary size of the data-set is unknown before the model is trained and evaluated for performance. Because of that, outsourcing of the creation of custom data-set could be very expensive. In order to use an existing data-set for the training of the model, a data-set for very similar use-case has to be found regarding a very similar environment. If a training data-set deviates too much from the input ultimately used for prediction (predicting trees in Mali), the predictions can turn out to be very inaccurate. After extensive research, a suitable data-set has been found. In order to use it for training, extensive pre-processing had to be applied, both to the training data-set and ultimately to the prediction input in order to make them as similar as possible. This is discussed in detail in subsubsection 5.4.4.

5.3.3 How to approach system architecture? The ambition of the stakeholders goes beyond just one research project, based on that there were some requirements. One of the criteria for this research were delivering a solution proposal and a working prototype demonstrating the functionality. Another criteria was to conduct a research, that can be extended by future work. In order to do that, this project should provide a well established starting point. In order to do that, the product of this research should be easily maintainable and extendable. Based on these expectations a decision on the system architecture had to be made, as shown in Figure 7.

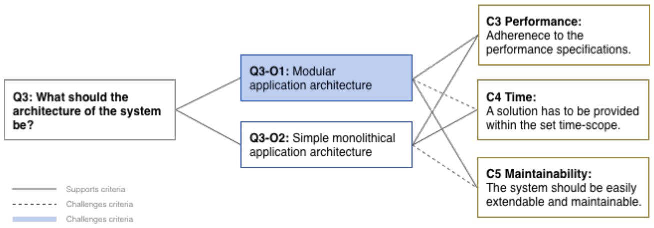


Figure 7: QOC diagram for application architecture

- **Q3-O1 Modular system architecture:** Structured modular structure of individual single-purpose application modules.
- **Q3-O2 Simple monolithic system architecture:** Easy and fast prototype solution fulfilling the functional requirements.

Rationale for choice Q3-O1: Based on the iterative experimental methodology, a modular system has been selected as more suitable approach.

Even though a monolithic system would be faster and easier to develop, there are serious concerns about maintainability and extendability of the final system. This is mainly because of the complexity of the whole system which is further described in subsubsection 5.4.1 describing final system architecture in detail. Thanks to the modular approach, it is easy to improve individual components in each iteration of the research as needed, without the need to modify the whole system. In addition the use-case of automation of periodic tree cover analysis can be satisfied.

5.4 System development

The development across all iterations will be described. This description will cover the challenges encountered, the rational for change in the upcoming iteration and finally comparison of the different approaches taken. The first iteration was to validate the basic approach of using machine learning algorithm for predictions and web user interface for the user to interact with the application. After feedback of the stakeholders, both the predictions algorithm and the web interface was improved.

Based on the requirements and available data, machine learning techniques (ML) are utilized to make the tree predictions. In the first iteration, I have decided to implement simple deep neural network (DNN) to validate the use of ML techniques for this context. This decision was based on previous research regarding the use of DNNs [33][18]. A simple prototype web user interface was develop in order to interact with the predictions system. As described in the upcoming section, the predictions algorithm identifies trees in the whole satellite image provided and saved this global prediction image. The predictions are made on a global scale beforehand, inn order to allow for fast analysis of specific regions, user defines area of interest (AoI) in the web application on the map. The user just requests analysis results on that specific region. The request is sent to a server where a local analysis for that AoI is executed and results presented to the user.

After validating the results and collecting feedback from the stakeholders, improved version for both the web application and recommendation system has been build. The web application is made more user friendly and additional futures get implemented. The recommendation system is changed from the proof of concept DNN, to more complex convolutional neural network (CNN) [37]. Where DNN algorithm considered only the values of each pixel separately, the CNN approach not only considers the values of that pixel, but also takes into account the neighbouring pixels, so shapes can be recognised. In summary, this is very important in this context, since the a pixel has a higher chance of being a tree pixel if it is next to another tree pixel. This approach is very well suited from this task as previous researches in similar domains have demonstrated [38][42][24].

5.4.1 Architecture. The system had to be designed in such way, that it is easily possible to extend the system with further functionality. This is mainly because this research only focuses on tree cover analysis and counting of individual trees, but doesn't compare the findings across different images on temporal basis. This is mainly due to the available data limitations (as described earlier) and project time constraints. Modular architecture is also a suitable approach in combination with the chosen methodology and the iterative nature of the research, where it should be easy to improve and replace individual modules of the system.

The final analysis tool utilizes 4 systems (modules) and one database, that are fundamental for the operation. The *Predictions Server*, where the predictions about trees for the full image are executed. These predictions are only executed once on the whole image and uploaded to the *Database* (DB). The *Analysis Server*, where the predicted image is requested from the DB and analysis only for the desired area of interest is computed. For this computation, the *Earth Engine API* is used, which runs in the cloud and return the requested analysis results. Finally the *Web Application Server* for hosting the website which is provides the user interface (UI) to the user in order to interact with the system. The whole architecture is depicted on Figure 8. The execution can be divided into 2 cycles. Once new satellite image is uploaded to the DB, the Predictions Server identifies tree cover on the whole image and saves this prediction back to the DB. The second cycle (local analysis) is when user requests analysis on AoI. The requested AoI coordinates are send to the Analysis Server (1), the prediction image is requested from database (2)(3), and the analysis is run using the Earth Engine API (4), the response is send to the Analysis server (5) and back to the Web server (6). The local analysis cycle is denoted by the numbers in Figure 8. All of the servers are deployed to a server-less execution environments, which means they do not exist if there are no requests they need to execute and only spin-up if a request arrives. This approach saves a lot of cost because the servers do not cost any money if they are inactive. This is further described int the sustainability section, subsection 6.1. The Production server is used only if new satellite image is provided for analysis. During the research only 1 image was available, because of that as the prediction has been already made, this server is no longer used.

5.4.2 Technologies. The user facing Web Application is build using the JavaScript framework React. Client-side technology was used because the likely inconsistent internet connection the users might be facing. The Analysis Server is a Node.js Express server. As a substitute for the Production Server, I used the Python Google Colab execution environment because it offers very high performance environment free of charge which is well suited to make

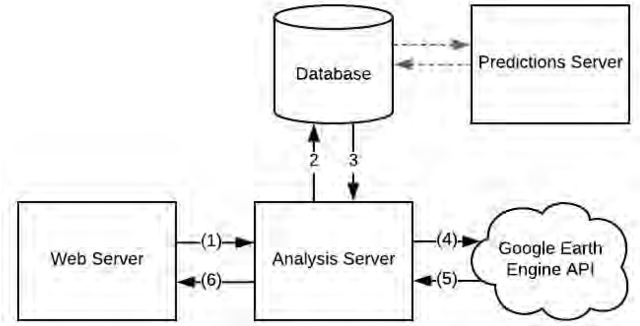


Figure 8: Tree analysis system architecture

machine learning predictions. For the machine learning model, the TensorFlow framework was used.

During development, the JavaScript-based Google Earth Engine code development environment was used to help with visualization and image analysis.

5.4.3 Data. This research is focused on how to use high-resolution satellite imagery for tree monitoring in the scale of individual trees. For this purpose, as already described in subsection 3.2, I am relying on the unique spectral signature of trees [9]. The WorldView-3 sample image used for this research encodes 8 spectral bands as 2.2 meters per pixel resolution.

In the first iteration, in addition to the available bands, one more band is artificially engineered based on arithmetic of the existing near-infrared and red bands. This new band is the Normalized difference vegetation index (NDVI) [41] and is calculated as follows:

$$\mathrm{NDVI} = \frac{\rho_{\mathrm{nir}} - \rho_{\mathrm{red}}}{\rho_{\mathrm{nir}} + \rho_{\mathrm{red}}} \tag{2}$$

The values of the 9 bands are afterwards normalized between the values 0 and 1 in order to increase the performance of the neural networks used for prediction [44].

Iteration 2. For the second iteration, more engineered features are added to highlight the the tree and vegetation related pixels. Based on previous researches, 4 new indexes have been created that help highlighting the tree related pixel based on spectral reflectance. One of them is the *canopy chlorophyll content index (CCCI)* used in remote sensing analysis of wheat [14]. Another one is *normalized difference water index (NDWI)* designet to sense vegetation contained liquid [16]. The last two are *enhanced vegetation index (EVI)* and *soil-adjusted vegetation index (SAVI)* which is similar to NDVI but considers additional wavelengths for correction [34].

5.4.4 Training Data. For the predictions, unsupervised artificial intelligence (AI) algorithms are used and thus a training data-set is needed. The purpose of the first iteration was to validate this approach with a quick experiment on very small training data-set with simple deep-neural-network (DNN). A training data-set of 160 hand picked data-points was constructed. 80 of the data-points represent tree pixels, 80 represent any other pixel that are not trees. Each of the data-points in the training data-set is associated with a value for each of the 9 futures (8 spectral bands + 1 engineered NDVI feature).

Iteration 2. In the second iteration, the original DNN based prediction system was changed for a more complex convolutional neural network (CNN). The rationale for this decision is discussed in the upcoming section [39]. For the CNN model, new type of training data is necessary.

As the new prediction network uses images for training, not only individual points, it was necessary to train the network on pairs of map tile and mask tile. Where the mask tile identifies the tree cover in the provided map tile, as shown in Figure 9. For this purpose an existing data-set has been used. This data-set was published by the Defence Science and Technology Laboratory agency part of a Kaggle challenge [1]. From this data-set, 189 unique image tiles (258 x 258 pixels) have been selected as most relevant for use in this project. The selection has been conducted by manually comparing the training data-set with the landscape of Mali in Africa. The training images encode 8 spectral bands, same as the Mali prediction image. As described in previous section, 5 indexes were engineered which in totals gives 13 feature bands for each pixel. Because the images used for training of the model are a little different from the image that will be used as the input to make the predictions on, both images had to be matched to be as similar as possible. For this purpose, as mentioned before, only relevant training images were selected from the data-set, and both the selected training images, and the image used for prediction, were normalized. To normalize the values between 0 and 1, *min-max scaling* was applied, where as *min* the 5th percentile of the values was used, and as the *max* the 95th percentile. This way the extreme outlier values were removed. This formula is described below as Equation 3.

$$\mathrm{n(x)} = \frac{x - P_{5th}}{P_{95th} - P_{5th}} \tag{3}$$

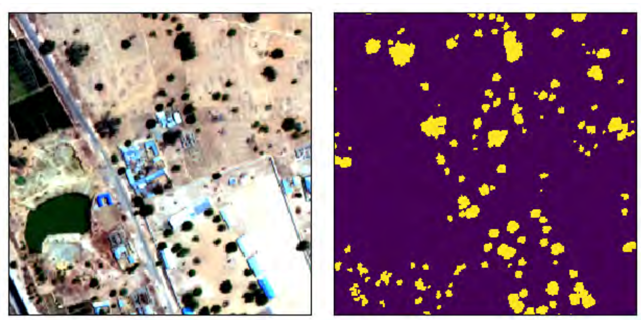


Figure 9: Training data example, map-mask tile pair

5.4.5 Prediction model. As mentioned in the subsection 5.4, the prediction model in the first iteration was a simple DNN which predicts each pixel independently without consideration of neighbouring pixels. The model consists of 4 hidden layers with 5,7,7,5 nodes respectively, dropout 0.1, input with 9 nodes (representing 8 bands + NDVI engineered band), and an output layer with the probability of the pixel being a tree pixel between 0 and 1. The architecture is visualized in Figure 10. The model is trained on 160 labeled data-points.

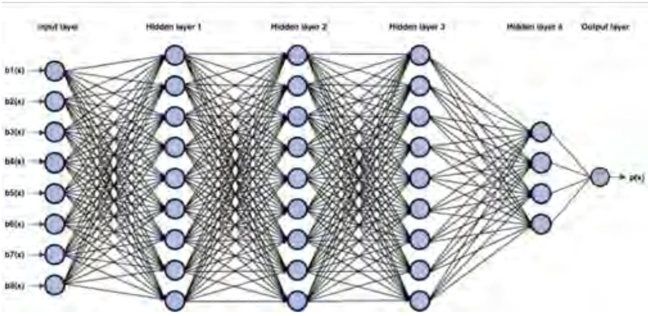


Figure 10: Architecture of the DNN model

The pixels are after prediction combined again into original form to represent an image of probabilities with values between 0 and 1. A binary image is constructed based on the predictions. The values above the threshold of 0.9 are converted to 1 (representing tree pixel), those pixels below the threshold are are set to 0 (representing background). In the binary predictions image, the background pixels are masked so that the original image is visible. This post-processing process is depicted in Figure 11.

Figure 11: Post-processing process from predictions to mask

It became obvious that the DNN network identifies few pixels of most trees fairly successfully, but underperforms in identifying all of the pixels of the trees. This is a good indication that a CNN network, which considers the surroundings and shape should be an improvement.

Iteration 2. In the second iteration, the simple DNN network was replaced with more advanced CNN network, as mentioned before in subsection 5.4. In particular a Fully Convolutional Network (FCN) with a U-Net architecture [37][36]. The U-Net architecture was introduced as state of the art approach to for image segmentation in the biomedical domain. It's advantage is that it implements so-called "skip connections" which in addition to the deep structure which helps extracting the information, also captures the location of that information within the image. This makes it very well suited for recognising trees in images and also capturing their precise location within the image. The architecture is visualized in Figure 12. More than 30 different model architectures were tested and compared for performance. The best performing model had the following aspects. The depth of the U-Net was established to be 5 levels, each level contained 2 CNN layers (both in the encoding and decoding part). The number of filter increases 2-fold as deeper the CNN layers are, which makes the number of filters in the levels 16,32,64,128,256 in the encoder and in reverse in the decoder part of the network.

The ELU activation function was implemented, in order to help with the dying RELU problem [10]. After every CNN layer, a batch normalization layer was applied to achieve better performance [20]. The final model was trained for 3000 epochs and the following hyper-parameters were chosen: Adam optimizer, learning-rate 0.1, batch-size 25, binary-cross entropy as loss function and 189 steps per epoch.

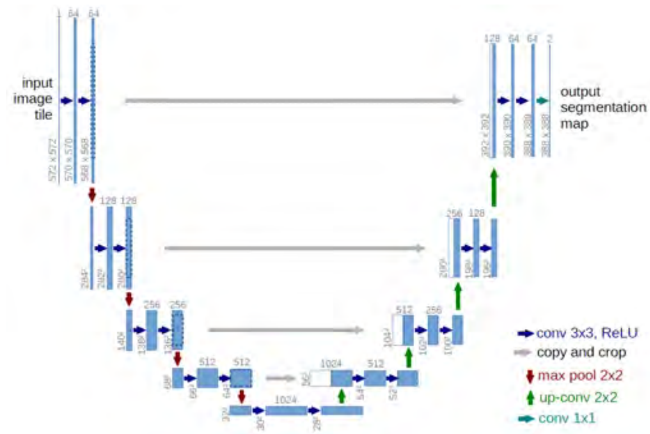


Figure 12: U-Net architecture [36]

Because the input for the model are tiles, the prediction image needs to be sliced up into those tiles of specific dimensions. When using model which had tiles of dimension 256x256 as input and made prediction for the whole tile (output 256x256 as well), there was a big decline of prediction accuracy along the edges of the tiles. In order to remove this limitation, image is sliced into tiles with overlap of 1 pixel on each side so that the input dimension is 258x258 but prediction is made just for the tiles the model has full information, see Figure 13. This means the output has size 256x256, which means it's not predicting values for the padding. This asymmetric approach improved the accuracy of prediction along the tile edges significantly.

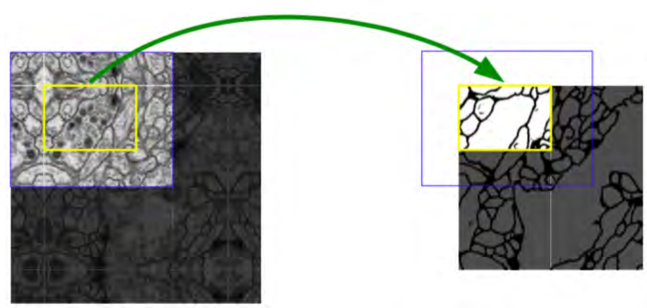


Figure 13: The input image padding strategy to improve accuracy along edges [36]

To train the model, data augmentation was implemented to enlarge the data-set of 189 unique 258x258 training tiles. This was three-fold, rotation, vertical flip and horizontal flip. For every image received from the original data-set, there was a 50% chance to be randomly rotated by either 0°,90°,180°,270°. Additionally, every image had a 50% chance of being flipped vertically and 50% chance of being flipped horizontally. All the modifications together, artificially expand the data-set 16-fold, from 189 tiles, to unique 3024 tiles.

During and after training, the model was validated on 1 manually created grand truth mask for an image tile from the satellite image of Tominian area. As the validation metric, the Jaccard similarity coefficient was used, in Equation 4 y represents ground truth prediction mas and ŷ represents prediction made [43]. Simply put, this coefficient quantifies how well do the ground truth mask and the prediction overlap.

$$jaccard(y, \hat{y}) = \frac{|y \bigcap \hat{y}|}{|y \bigcup \hat{y}|} \tag{4}$$

5.4.6 Web application. For the purpose of interacting with the predictions model and request analysis based on area of interest (AoI), a web interface had to be created. As described in the requirements, the web interface. The web interface enables users to draw a polygon to select AoI for analysis, sends the coordinates to the analysis server and receives results, including map overlay with highlighted canopy cover as shown in Figure 16.

The web server relies heavily on the analysis server, which executes all the AoI based predictions. The whole application is build as a Earth Engine application which uses Google Earth Engine API (EE) so all of the heavy computations are executed on Google servers. In order to use the application user has to log-in with a Google account that is registered for the EE services. This is a limitation which was not considered important in the first iteration.

The analysis server uses the full prediction image to do the AoI analysis. It is a Node.js Express server running on Google Cloud as server-less function. The prediction image is image with pixels of value either 0 (background) or 1 (tree). In order to count the trees, this image is vectorized within the AoI bounds, which turns touching pixels into single shape, denoting 1 tree. This way, it is possible to count the number of shapes in the AoI and thus get the number of trees. The analysis server also calculates the area covered by tree pixels and the total area and sends the statistics including the tree count back to the web application. The architecture in detail is described in subsubsection 5.4.1 and is visualized in Figure 8.

Iteration 2. In the second iteration, the new requirements shifted the focus on making the interface more user friendly. The EE application got registered as standalone service so it was not longer necessary to log in with supported account so anyone could use it easily. New, user friendly design was implemented as well as the stakeholder requirement of providing French user interface (one button to change language between English and French). These improvements made the application much easier to use for the stakeholders. New requested futures were implemented, like displaying the analysis result of are cover in 2 units of measurements (squared meters and hectares). The future of showing the AoI polygon coordinates, and exporting the analysis results including the coordinates were added as well. The new version of the web application is shown in Figure 17. The new version was also made with mobile devices support. That means analysis can be requested on mobile phones and tablets and the results are displayed directly in the device inside the optimized interface. The mobile user interface is presented in Figure 18. The application was coded in the JavaScript React framework and hosted on Google Cloud AppEngine. This choice was made, because the users in Africa do not always have stable internet connection, this technology executes a lot of the functionality locally without the communicating with the server (like switching the language).

5.5 Testing and evaluation

5.5.1 Web application. Because of the utilized methodology and iterative approach, validation and feedback on the web interface has been received during research. After the first iteration, the stakeholders evaluated the presented solution as fitting for their use and proposed improvements for the next iteration. These new requirements were noted (subsection 5.2) and later implemented. Full scale testing was not yet conducted because of the time constraints. To assist with the future testing a feedback for was implemented into the web application in order to receive fast feedback from the users.

5.5.2 Prediction model. The performance of prediction model was evaluated based on one validation mask tile. This validation mask tile was created by hand and represents the ground truth of the trees predictions. Ground truth mask is shown in Figure 14d. The prediction results, are displayed in Figure 14. This array of images includes the raw prediction probabilities (b), the binary prediction (c) derived by post-processing and an overlay of the prediction mask over the original image (e). It is very hard to determine exactly the accuracy of the prediction system, since the satellite images are the only source of information and it is impossible even for humans to confidently tell what are trees and what not. Prom the presented validation image Figure 14e it can be observed, that X trees were miss-classified. According to the ground truth, there are 146 trees in that image. This makes the error in count of the trees around 2%.

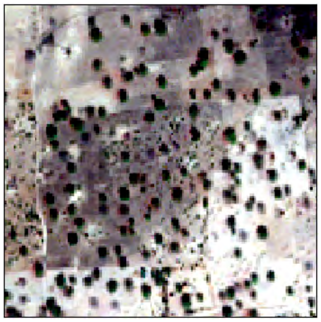
A quantified score for the validation image is calculated by the Jaccard similarity coefficient, as mentioned in previous sections. The coefficient has the value 0.46 when comparing the post-processed predictions with ground truth. This is considered a very good result compared to previous version of the prediction algorithm. The biggest weakness of the model is that it has been trained on different data-set, than is used for predictions. During the training the accuracy of the model got up to 92.5%, as visualized on Figure 15.

6 SUSTAINABILITY FUTURE WORK

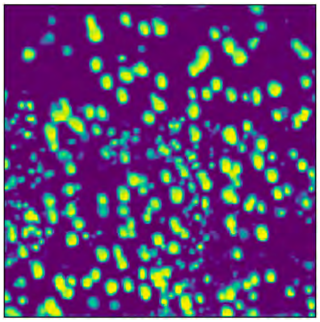
6.1 Sustainability and cost

In regards to ICT4D projects, sustainability is one of the key measurements of the success of the whole project. The sustainability aspects have been considered throughout the whole research and decisions have been made to support the environmental, social and economic sustainability [31].

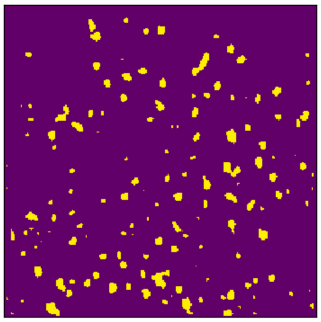
6.1.1 Environmental sustainability. The whole project is centered about using remote sensing technologies to monitor large areas. The environmental impact of such approach is much smaller compared to other methods, like using human labour to achieve similar results. This is thanks to the fact, that using this system, it is possible to analyze areas of hundreds of hectares automatically within seconds.



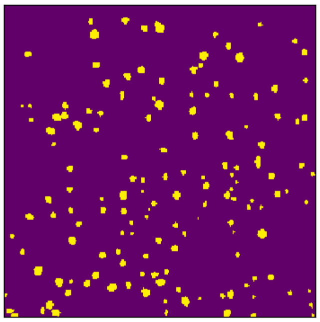
(a) Original image



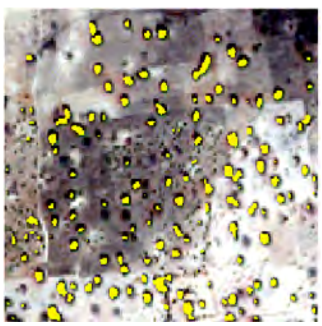
(b) Predicted probabilities



(c) Predicted trees binary mask



(d) Ground truth mask



(e) Prediction mask overlaying image

Figure 14: Comparison of predictions with ground truth

The environmental sustainability was also considered during the technological implementation of the solution. The application is hosted on the Google Cloud. This choice was made because it is carbon neutral and the energy consumption needed to run the data-centers is 100% offset with renewable energy [2]. Not to waste the energy, the architecture of the developed tree monitoring system, is based on the server-less approach which means the service is not running unless it is being used and scales automatically depending on the load.

Besides the direct environmental impacts of running the system, the use of the system itself is to monitor trees in the Tominian region in Mali Africa. I hope that, through the use of the system, actions will be take to improve the less than ideal conditions regarding trees and forest in the region.

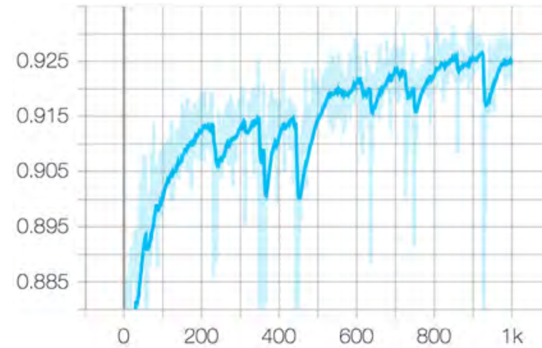


Figure 15: The accuracy of the prediction model on the training data-set throughout the training

6.1.2 Social sustainability. In order to support communities and ICT4D development, the developed in regards to this project, is published under an open-source licence on GitHub.com and is publicly accessible to anyone.

The open-source initiative hopes to fuel the interest in developing IT solutions with social impact.

6.1.3 Economic sustainability. In regards to the economic sustainability, the developed system has been designed to operate with minimal cost. As mentioned in previous section the system is hosted in Google Cloud. The current implementations allows the system to operate within the free tier category, which means the expenses of running the system are 0 euros.

The one big expense, is the cost of purchasing new satellite images, when new predictions on updated images need to be made.

6.2 Future work

This system can used as a great inspiration for anyone interested in the remote sensing research and ICT4D projects. It is greatly encouraged to build on top of this project and extend the tool. As soon as the stakeholders decide to use this system, only the satellite imagery for analysis has to be purchased, otherwise the system is ready to be used. The need for expensive satellite imagery is probably the biggest challenge of this project. Because of the need for very high resolution imagery, no other alternatives have been found during the research.

There are many possibilities how to extend this research and improve the system. As mentioned before, the ambition of the stakeholders is much bigger than what was possible to accomplish during this research. The ultimate goal is to be able to reliably count not only free standing trees but also trees in forests, compare the counts in between images from different time-points and identify incidents like illegal tree cutting. Other use-cases could involve monitoring the development of tree covered area on long-term basis.

The next steps that should be taken to improve the solution developed in this research would be improving the accuracy of the prediction system by training the prediction model on a data-set, that is more similar to the tropical savannas biome. Another point for improvement would be counting the trees from the predicted segmentation maps, currently the system is relying on the fact that pixels of the individual trees are not in direct contact with each other. This could be solved better with own neural network focused on counting the trees within the predicted segmentation masks.

To asses the reliability of the system, a detailed evaluation still has to be conducted.

7 CONCLUSION

This research presents a fully functional solution including a prototype on how to use satellite images to analyze trees in the Tominian region in Mali Africa. The time scope of the research, and the available data unfortunately did not allow to identify illegal tree cutting for reasons discussed in the previous sections. However this research has successfully delivered a prototype tool for tree analysis and has set the directions and solid starting point for further research to reach the ambitious goal. The presented solution uses semantic segmentation and machine learning algorithms to execute analysis on the satellite image and present the results in a intuitive web application optimized not only for desktops but also for mobile devices. For this purpose the U-Net architecture of convolutional neural network proved to be a very good technical solution. The system analyzes the canopy cover within the area of interest, compares the result with the total area and estimates the tree cont within the region. All of the results can be easily exported for future reference.

The system is very good at analyzing the area covered by trees and visualizing the results. The solution for counting trees, focuses on free standing trees and experiences a notable decline in tree count accuracy once tree canopies are in direct contact. This is considered the biggest limitation of the current system. The focus was also on identifying what other data could help with the accuracy of the system, but as expected, the satellite imagery training and prediction data seems to be of the biggest importance.

Findings and results of this research should be a great starting point for any future research in the domain of vegetation analysis using remote sensing, and generally many other ICT4D projects.

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APPENDIX

Figure 16: System prototype version 1, desktop web interface

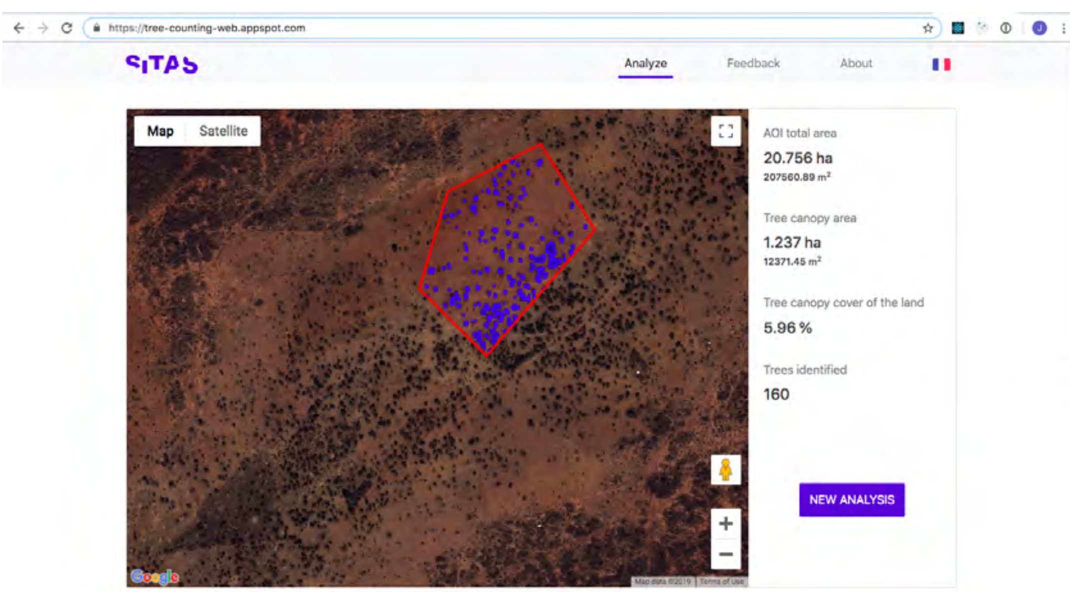

Figure 17: System prototype version 2, desktop web interface

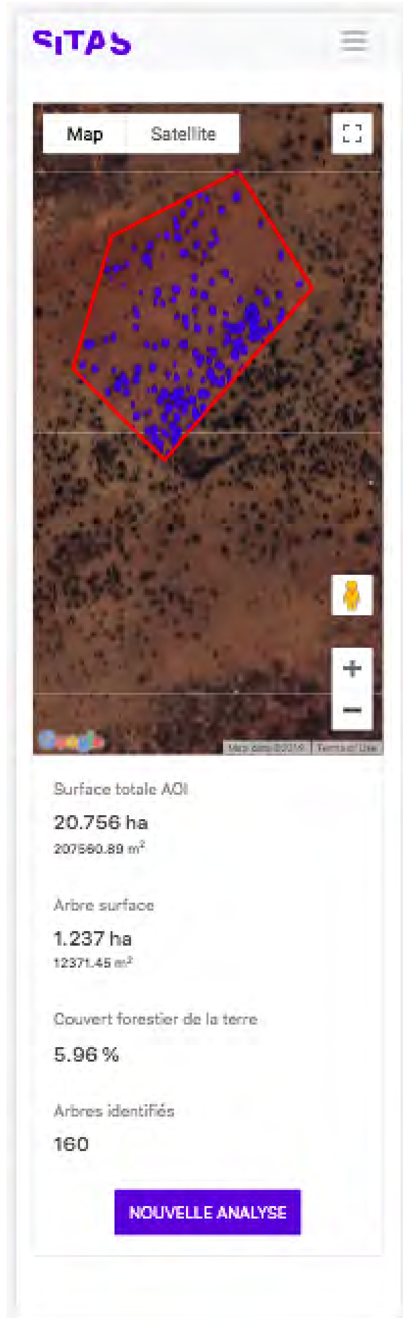

Figure 18: System prototype version 2, mobile web interface