Modeling the Customer Experience Using Machine Learning for Optimizing the Performance of Telecommunications Networks: Case of Mobile Networks

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Abstract

Customer experience is a major issue for telecommunications companies seeking to offer quality and personalized services in an environment where customer expectations are constantly evolving. Measuring this experience is a complex challenge, particularly with regard to the impact of network performance on customer usage and, consequently, on their satisfaction. In this context, an in-depth analysis on the relationships between network performance indicators and customer experience was carried out in the network of the telecommunications operator Orange Cameroon (OCM). A method based on machine learning and deep learning was used to predict the behavior of network performance indicators. QoE value thresholds and network performance indicators have been defined for different levels of customer satisfaction. A machine learning model made it possible to obtain precise predictions of customer satisfaction. The results obtained showed that customer satisfaction can be reliably predicted from network performance indicators and QoE. This approach offers a better understanding of the customer experience and allows telecommunications operators to act proactively to improve user satisfaction across all actions related to their use. The application of the results of this study presents a significant impact at different levels. At the national level, telecommunications operators can optimize their services and react more quickly to network incidents, thus improving customer satisfaction and loyalty. This strengthens the competitiveness of telecommunications companies by providing a better customer experience. Globally, a better understanding of customer experience is driving the evolution of the telecommunications industry as a whole

Keywords: customer experience, performance indicators, machine learning, deep learning, customer satisfaction, quality of service

1. Introduction

In the field of telecommunications, the rapid evolution of technologies and the growing demand for connectivity have led to increased attention to customer experience in order to ensure alignment between customer satisfaction and the services provided [1]. Understanding this experience in depth and developing scientific models to evaluate and predict customer satisfaction based on network performance have become major research priorities. The performance of telecommunications networks plays a crucial role in customer satisfaction. High speeds, low latency, optimal voice and video quality, as well as reliable connectivity are all criteria that influence the user experience [2]. Therefore, it is essential to be able to objectively measure this performance and understand how it is perceived by users. In this context, our work focuses on developing models and methodologies to evaluate and predict customer satisfaction based on network performance. These models rely on objective indicators such as quality of service (QoS), which encompasses metrics such as bandwidth, delay, mean opinion score and packet loss [3]. However, QoS alone is not enough to capture the subjective dimension of the user experience.

This is why researchers are increasingly turning to quality of experience (QoE) to assess customer satisfaction more holistically. QoE takes into account subjective aspects such as the perception of audiovisual quality, the ergonomics of the user interface and the ease of navigation [4]. It also integrates contextual factors such as the type of service used, the usage environment and the specific expectations of each user. QoE measurement relies on rigorous scientific approaches, such as experimental studies, user surveys, statistical analyzes and prediction models [5]. Researchers use these methodologies to collect objective and subjective user experience data, analyze it, and draw conclusions about customer satisfaction.

In the OCM context where our work was carried out, the measurement of the quality of the customer experience is carried out by applying precise formulas to data from sites and customers. An administrator takes care of manually running queries every day to extract the QoE values for the previous day. These values provide indicators on the quality of Voice, SMS and DATA services by focusing on the success rate of access to these services and without taking into consideration the voice of the customer. Measuring customer satisfaction with their uses thus becomes an arduous task for the team in charge of QoE who, despite their ability to calculate this QoE and analyze it, cannot answer the fundamental question «**is the customer satisfied?** ». The main objective of this work will be to measure customer satisfaction and their experience while using the network, taking into account network performance indicators.

2. QoE in telecommunications networks

2.1. Importance of QoE

The importance of Quality of Experience (QoE) among telecom operators cannot be underestimated. In an increasingly connected world, users expect high-quality telecommunications services to meet their needs. QoE plays a central role in the growth of businesses and telecommunications companies. Users have become more demanding and more aware of the quality of the services they use. If they are not satisfied with the QoE provided by an operator, they are likely to turn to other options. QoE is the measure of a user's overall level of satisfaction with a service, from the user's own point of view [4]. This goes beyond simple objective network performance parameters (quality of service or QoS) and encompasses subjective user experiences, including physical, temporal, social and economic factors. Figure 1 presents the different elements involved in the QoE of a telecommunications network.

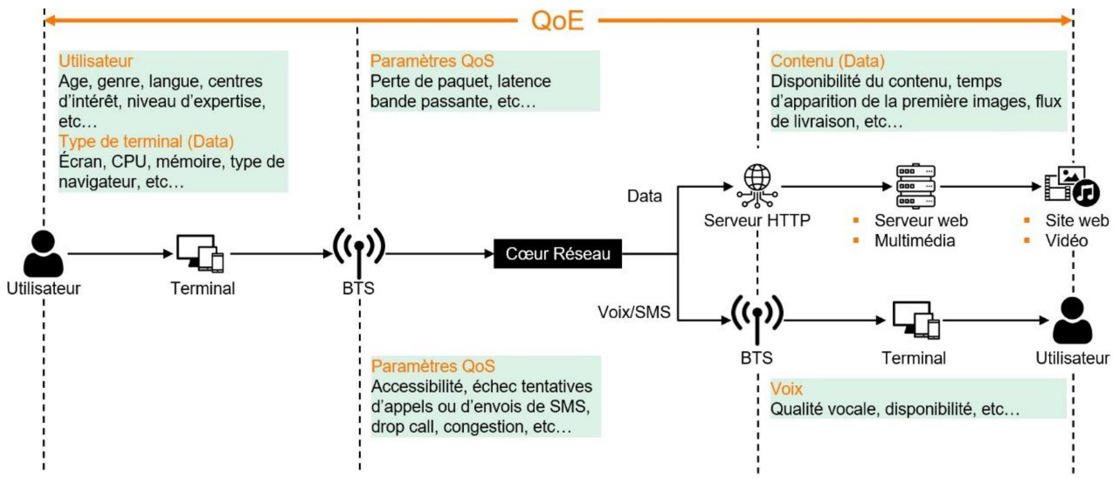

Figure 1. End-to-end QoE

To ensure optimal QoE, telecommunications operators must understand the needs and expectations of their customers. This involves collecting QoE data using appropriate monitoring tools and analysis mechanisms. Network performance parameters, such as network availability, accessibility, continuity and integrity, among others, are key elements to monitor to ensure satisfactory QoE.

QoE therefore impacts aspects such as:

- Customer loyalty: Indeed, the more satisfied a customer is with the services offered to them, the more likely they are to remain loyal to the current operator, the latter thus retaining the turnover provided by this customer.
-
- Reputation: When a customer is satisfied with his uses, it is likely that he will be able to positively recommend the brand to people close to him, thus contributing to the increase in the company's customer base and the perception of the brand. company in the market.
-
- Competitive differentiation: In a competitive sector, offering superior QoE allows you to stand out from other operators. Customers seek quality services and are ready to change operator if they are not satisfied.

2.2.*Factors influencing QoE*

Several factors can influence QoE in telecommunications services. We can classify the elements impacting QoE according to three axes [6] as shown in Figure 2: The system, the context and the experience.

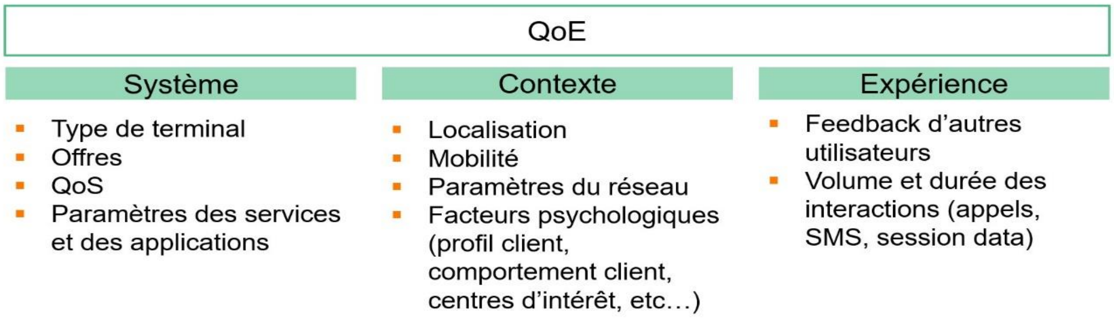

Figure 2. Factors influencing QoE [6]

2.3.Calculating user experience

At OCM, user experience is calculated for DATA, VOICE and SMS services. It can be evaluated and calculated from different network parameters. These parameters make it possible to measure the quality of service (QoS) offered by the operator and to determine user satisfaction. By analyzing and interpreting these metrics, it is possible to obtain an accurate assessment of the user experience.

In the case of voice, QoE can be evaluated based on the rate of successful calls. This parameter measures the proportion of calls successfully established compared to the total number of calls attempted. A high call success rate indicates good call quality, with satisfactory voice clarity and connection stability. Issues like dropped calls, distorted voice, or severe delays can lead to poor user experience and lower customer satisfaction.

When it comes to SMS, SMS hit rate is an important metric to evaluate QoE. It measures the percentage of SMS messages sent successfully compared to the total number of messages sent. A high SMS success rate indicates high reliability in message transmission, with fast and lossless delivery. Extended delivery times, unreceived messages or transmission errors can negatively impact user experience and customer satisfaction.

The method for calculating Voice and Message QoEs is illustrated in Figure 3.

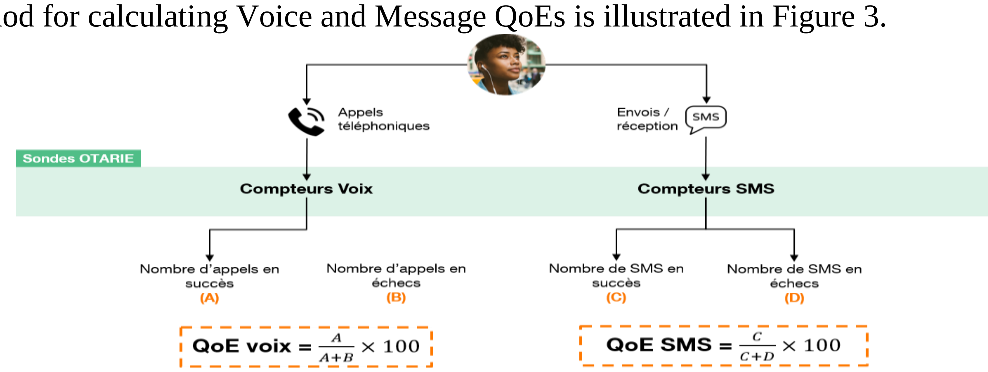

Figure 3. VOICE AND SMS QoE Calculation Method in Orange Cameroon [8]

To evaluate QoE in data, several key parameters can be considered as shown in Figure 4. First, Transmission Control Protocol (TCP) session counters can be used to measure the number of sessions successful when browsing the web, downloading files and streaming content. These meters help quantify the stability of the connection and the network's ability to provide reliable data transmission. A low session failure rate indicates a better user experience in terms of smooth browsing and uninterrupted content downloading.

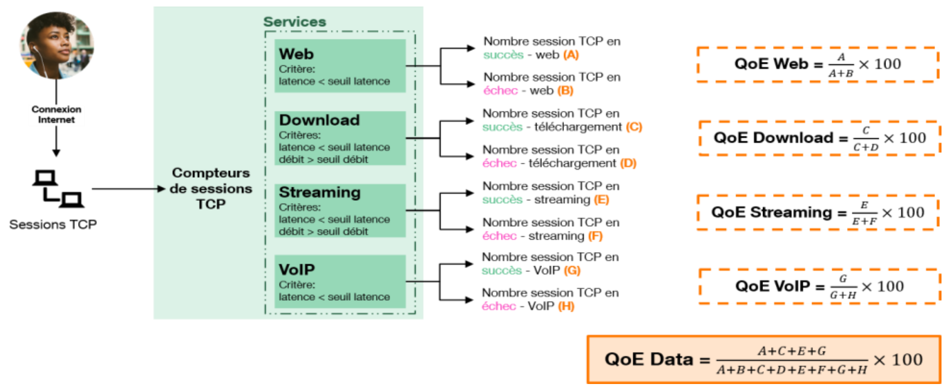

Figure 4. DATA QoE Calculation Method in Orange Cameroon [8]

Additionally, it is important to emphasize that these quantitative measurements alone are not sufficient to fully evaluate user experience. It is also essential to collect qualitative data, such as satisfaction surveys and feedback, to gain a deep understanding of customer needs and expectations.

2.4.The limits of QoE calculation

Assessing QoE is a complex challenge. Although network metrics can be measured, it is difficult to completely capture the user's subjective perception. QoE is influenced by individual factors such as personal preferences, expectations and previous experiences, making its objective measurement difficult to achieve. Indeed, Orange Cameroon calculates the QoE as presented in Figures 3 and 4, which does not take into account several elements as shown in Figure 5:

Figure 5. Factors influencing QoE: Case of Orange Cameroon [8]

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Furthermore, taking into account the calculation methods used, we note that the calculation of QoE does not take into account a set of performance indicators, in particular on network coverage, network availability and others.

3. Methods and Tools

3.1. Neural networks

Deep Learning was derived from the neural networks of the human brain which is truly complex. By carefully studying the brain, scientists and engineers have developed an architecture that could fit into our binary digital world. One of these typical architectures is shown in Figure 6:

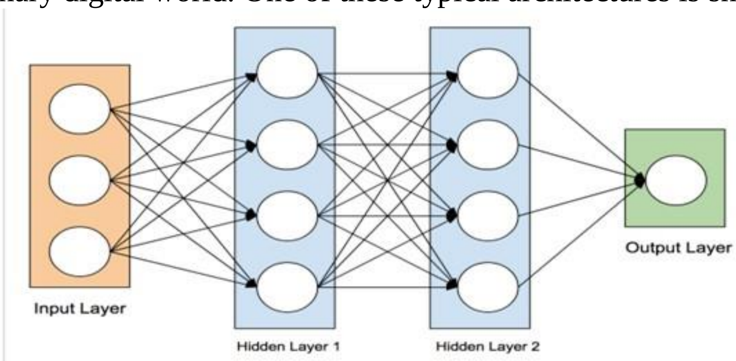

Figure 6 – deep learning network [9]

A neural network is generally made up of a succession of layers. This model includes [9]:
Three elementary operations: multiplication, summation and activation;
Input data which is consumed by the neurons of the first hidden layer. Each layer can have one or more neurons. The connection between two neurons of successive layers would have an associated weight which defines the influence of the input on the output of the next neuron and possibly on the overall final output. On each artificial neuron, each input value is multiplied by the corresponding weight. Then, the result obtained will be added to what is called the bias to apply an activation function to it at the end;

$$Y = f(\sum_{i=1}^{n} (\Omega i \times Xi + b) \quad (1)$$

Where:

- f: the activation function
- xi: an input;
- i: the weight associated with an input
- b: the bias

System Analysis

3.1.1. Functionalities

The main features of our application are [11]:

- Perform a forecast calculation of a set of network performance indicators: the user executes a set of procedures to determine the future values of performance indicators such as MOS, drop call rate, etc.

- Measure customer satisfaction: the user can visualize the a priori level of satisfaction of customers via sites through a map of the national territory.
- Manage built-in artificial intelligence models: the user adds models and modifies the models used by default.

3.1.2. Flowchart of methodological steps

The approach adopted given in Figure 7 for the realization of our solution is therefore as follows:

(1) We have studied and analyzed by several statistical methods (one-way analysis of variance, study of seasonality, distribution, etc.) all of the performance indicators used in this work in order to understand their essence.
(2) Analysis of the relationships between the different performance indicators: At this stage, we carried out a battery of statistical tests and a bivariate and multivariate analysis.
(3) At the same time, we designed and implemented a satisfaction survey on a small scale (employees of the Customer Experience Department) in order to collect data on customer satisfaction.
(4) Analysis of data collected during the satisfaction survey in order to understand the link between satisfaction declared by customers and network performance indicators.
(5) Using Machine Learning and Deep Learning frameworks, we designed a set of models:
(6) Inference model: Allowing MOS data from Voset robots to be inferred across all Orange Cameroon sites.
(7) Forecasting models: Allowing all performance indicators to be predicted over time. This is a set of 8 forecast models (one model per performance indicator).
(8) Classification model: Model allowing us to group our data into satisfaction classes.
(9) Using the Django framework, we developed the functionalities for visualizing the level of satisfaction, displaying forecasts and modifying models.
(10) Design of a Python API integrating all artificial intelligence models in order to integrate it more simply.
(11) Integration of the API into the application.
(12) In step 9, we trained our solution by performing performance tests. In the event that the results were not satisfactory, that is to say the application gave us inappropriate answers, we restarted at steps 5 and 6; otherwise, we got NetPredict, which is our working prototype for customer satisfaction prediction.

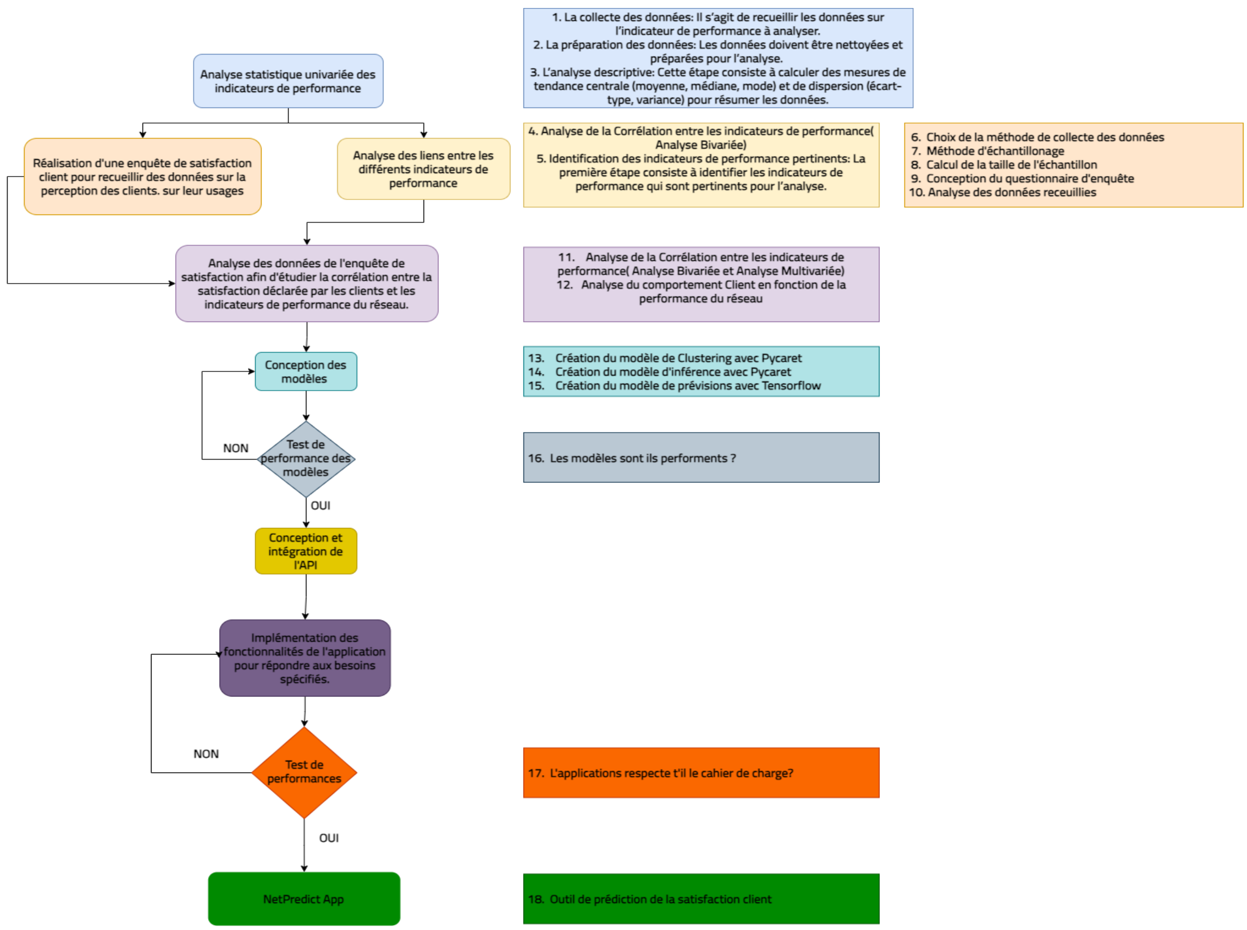

Figure 7. Flowchart of methodological steps

3.2.3. API design

Our API works from a set of machine learning and deep learning models:

- **Forecast model** : This is a deep learning model created with TensorFlow to make short-term forecasts of all the network performance indicators used in our work, with the aim of measuring future customer satisfaction. Orange Cameroon.
- **Inference model**: The MOS being an important performance indicator in the context of voice satisfaction, it therefore seemed important to design a model

3.3 Tool modeling

In this part, we will present the software architecture adopted as well as the different use cases and their modeling.

3.3.1. Use case diagram

The use case diagram is given by Figure 8

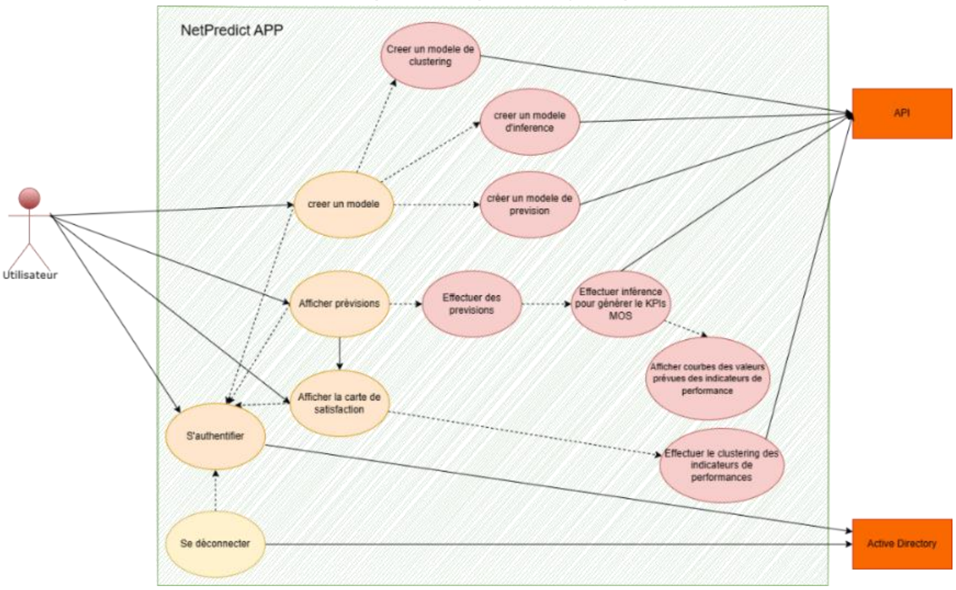

Figure 8. Use case diagram

3.3.2. Sequence diagram

3.3.2.1. Sequence diagram for the “Create Models” use case

Figure 9 shows the sequence diagram for the “Create Models” use case.

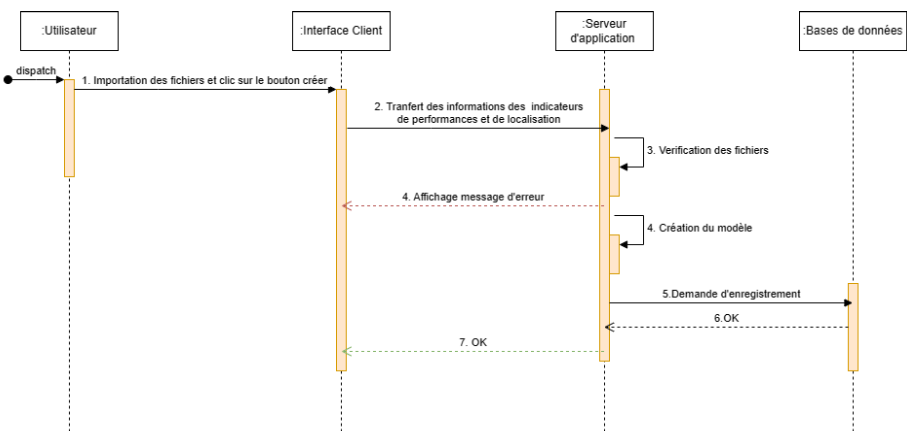

Figure 9. Sequence diagram for the “Create Models” use case

3.3.2.2. Sequence diagram for the "Viewing Forecast" use case"

Figure 10 shows the sequence diagram for the "Show Forecasts" use case.

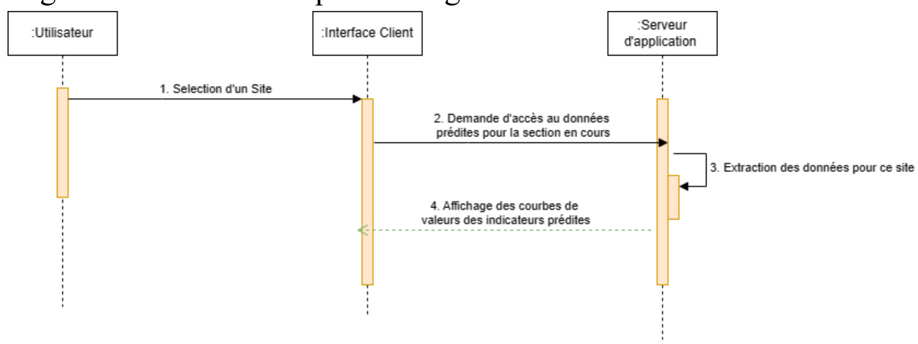

Figure 10. Sequence diagram of the "Displaying Forecast" use case

3.3.2.3. Sequence diagram of the "Show Map" use case

Figure 11 shows the sequence diagram for the "Show Map" use case.

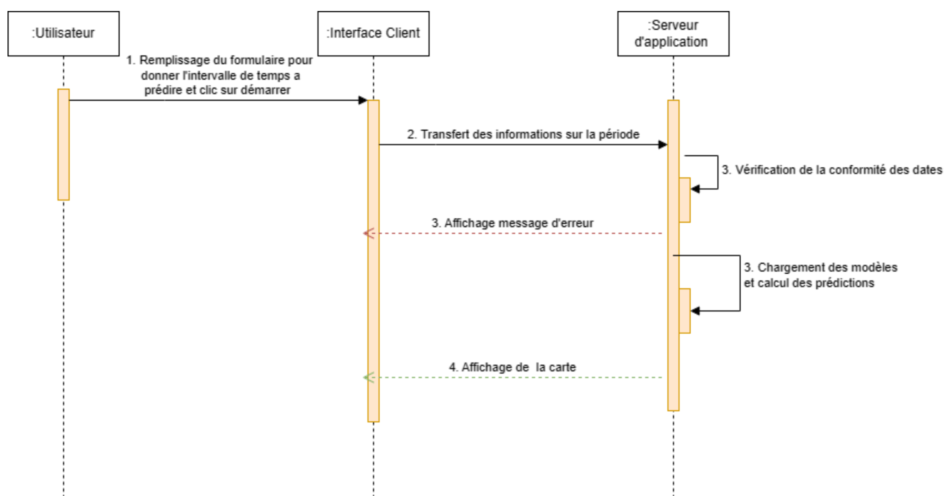

Figure 11. Sequence diagram of the "Show Map" use case

3.3.3. Class diagram

Figure 12 shows the class diagram of our tool.

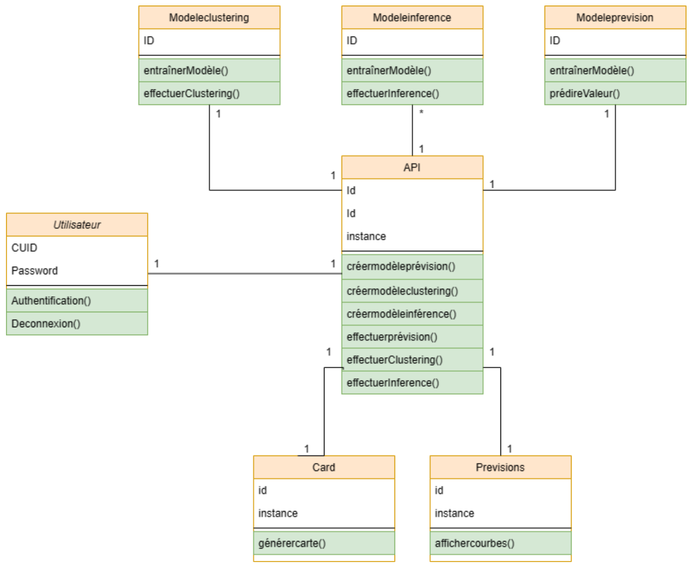

Figure 12. Class diagram

3.4 Tool design

In this part, we will present our challenges, the architectures of our solution, and the technologies used.

3.4.1. Constraints

Designing a customer satisfaction forecasting tool based on network performance indicators can present several challenges. Here are some of the main challenges:

- Allow you to take an .xls file as input containing the parameters used to train the models.
- Selection of relevant performance indicators, which requires in-depth analysis of available data, as well as an understanding of the factors that influence customer satisfaction.
- The design of artificial intelligence models capable of understanding the complex relationships between performance indicators and customer satisfaction, and generating accurate forecasts.
- Integration of models into the application to automatically generate customer satisfaction forecasts in real time.
- Evaluating and validating customer satisfaction forecasts to ensure their accuracy and reliability.
- Data Security and Privacy: Protecting customer data and complying with privacy regulations are significant challenges to overcome.
- Adaptability and scalability: The customer satisfaction forecasting tool must be able to adapt to changing needs and environments. It must be scalable to handle increasing data volumes and be adaptable to changes in performance indicators and customer requirements.

3.4.2. Technologies used

This is for us to present all of the software tools that we used to develop our tool.

3.4.2.1. Development tools

a. VS Code

Visual Studio Code is a simplified code editor, which is free and developed as open source by Microsoft. It works on Windows, macOS and Linux. It includes: support for several hundred programming languages, such as C, C, C++, CSS, HTML, Java, JavaScript, JSON, Markdown, PHP, PowerShell, Python, TypeScript, YAML, etc.

b. Git

Git is a DevOps tool used for source code management. It is a free and open-source version control system used to efficiently manage small to very large projects. Git is used to track changes in source code, allowing multiple developers to work together on non-linear development.

3.4.2.2. Programming languages

a) Python

Python is an interpreted, multi-paradigm, and cross-platform programming language. It promotes structured, functional and object-oriented imperative programming. The latter has strong dynamic typing, automatic memory management by garbage collection and an exception management system. Python runs on most computing platforms, from smartphones to mainframes. It is designed to optimize programmer productivity by offering high-level tools and easy-to-use syntax.

b) JavaScript

It is a programming language that allows you to create dynamically updated content, control multimedia content, animate images, and much more.The JavaScript language is mainly used to improve the ergonomics of a website and/or a user application interface.

3.4.2.3. Library

a. SQLite [12]

SQLite is a library written in C language which offers a relational database engine accessible using the SQL language. It is widely used for local data storage in many software and applications, including web browsers and mobile operating systems. The unique thing about SQLite is that it stores the entire database in a single file, making it easier to deploy and manage applications.

b. Bootstrap[13]

Bootstrap is a free and open-source web development framework. It is designed to facilitate the process of developing responsive and mobile-first websites by providing a collection of syntaxes for design patterns. Bootstrap offers ready-to-use components such as grids, forms, buttons, and navigation bars, allowing developers to quickly create attractive and user-friendly user interfaces.

c. PyCaret [14]

PyCaret is a Python library for data science and machine learning. It simplifies the machine learning workflow by providing features such as data preparation, model selection, cross-validation, hyperparameter tuning, and model evaluation, all in a single line of work. coded. PyCaret is ideal for data scientists and researchers who want to accelerate their model development process and get reliable results quickly.

d. TensorFlow[15]

TensorFlow is an open-source machine learning library developed by Google. It allows you to create and train machine learning models, with a focus on deep neural networks. TensorFlow is widely used in applications in computer vision, natural language processing, speech recognition, and many other areas of artificial intelligence. Its flexibility, ability to handle large data sets, and support for distributed computing make it a popular choice among machine learning researchers and practitioners.

e. Django [16]

Django is an open-source Python web framework that facilitates rapid development of robust and secure web applications. It follows the model-view-controller (MVC) principle and offers features such as database management, user authentication, forms management and dynamic content generation. Django is known for its ease of use, comprehensive documentation, and active community, making it a popular choice for web development.

f. GeoDjango [17]

GeoDjango is a Django extension that allows you to develop geospatial web applications. It facilitates the storage, query and manipulation of geographic data, such as GPS coordinates, geometric shapes and spatial operations. GeoDjango offers advanced features such as spatial indexing, map projection and integration with GIS (Geographic Information System) tools. It is widely used in the fields of online mapping, urban planning, logistics and natural resource management.

3.4.3. System Architecture

a) Solution architecture

We propose to implement an architecture consisting of the following elements: an application server in which the backend, the webview and our artificial intelligence API are hosted; an Active directory where all the information of the users of our tool and the database are recorded. Figure 13 illustrates the overall architecture of our solution:

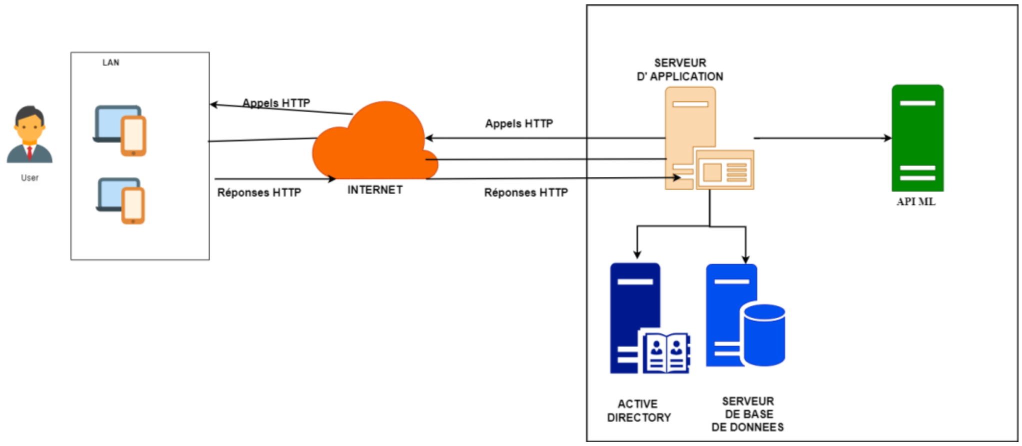

Figure 13. Overall architecture of the solution

b) Logical architecture of the solution
Figure 14 presents the software architecture of our solution. It highlights the software we used along with their versions.

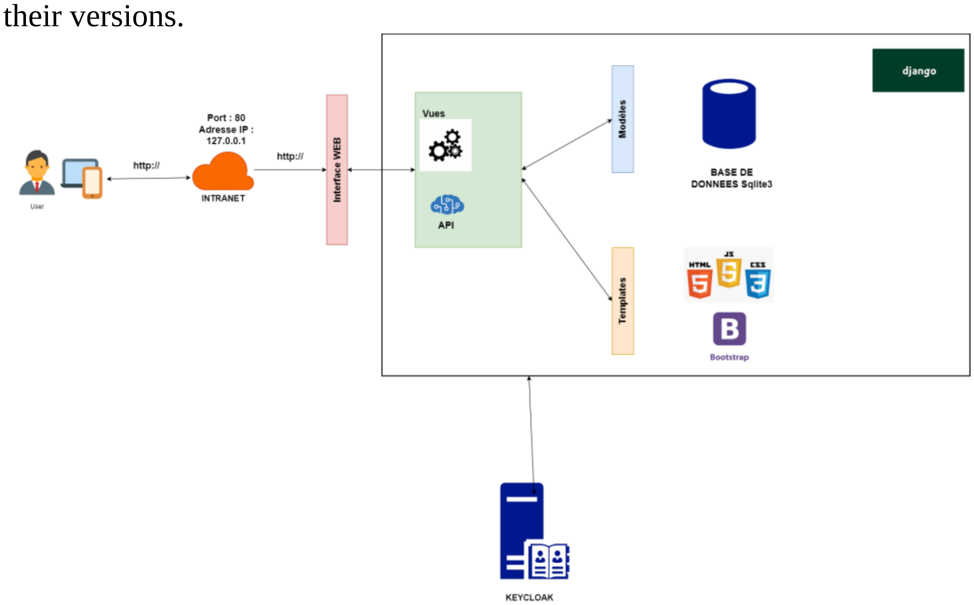

Figure 14. Logical Architecture of the solution

4. Results and Comments

4.1. Structural architecture of the application

Following the methodology presented previously, we were able to set up a tool for predicting customer satisfaction across the entire territory based on network performance indicators called NetPredict. The structural architecture of this is represented by Figure 15:

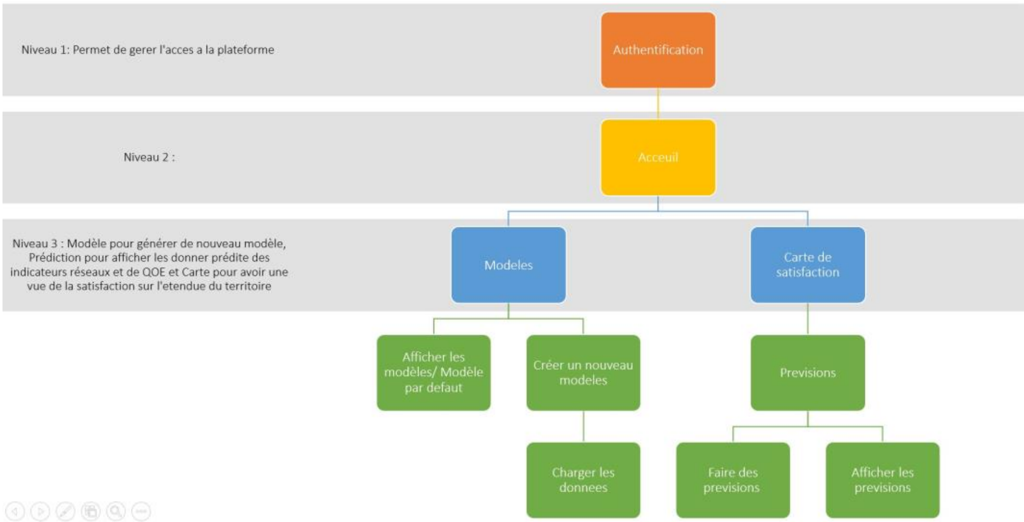

Figure 15. Methodology of the solution

Our NetPredict Application is structured as follows:

- **The authentication interface**: This is the entry page of the application on which the user authenticates
- **The home page:** On this page the user sees the default model that can be used immediately and the general presentation of the application
- **The Models interface**: This is the page that allows you to generate new artificial intelligence models and display a brief summary of the models created so far.
- **The Satisfaction Map interface**: This is the page that allows you to visualize the level of customer satisfaction across the national territory and to visualize the evolution of performance indicators over the chosen period.

4.2. Tool presentation

In this Part, we will present the different interfaces of our solution.

4.2.1. Interface « Home page »

If the CUID and password are correct, the user goes to the home page. Figure 16 below illustrates the home page.

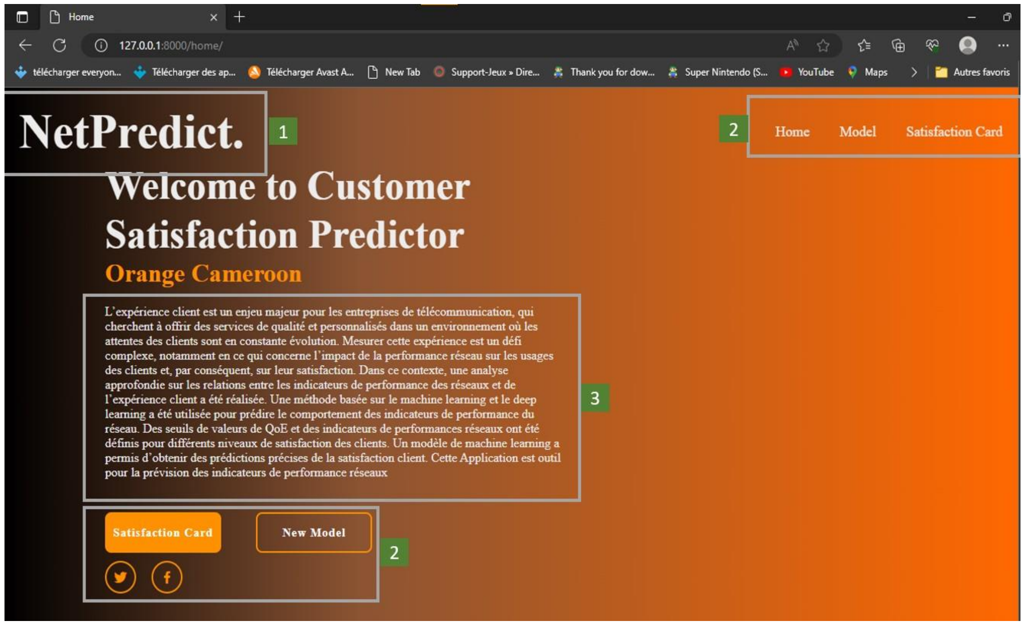

Figure 16. Homepage of Net Predict

Legend:

(1) This part presents the name of the application.

(2) This section corresponds to the menu which gives us access to the other pages of the application. We also have access to pages dedicated to Orange Cameroon to get a quick opinion on customer comments on the official Orange Cameroon pages.

(3) In this section, we briefly present the design reasons for such a tool and its main objective.

4.2.2. Interface « Models »

Figure 17 shows the model creation/update page. Here the user will have the possibility of re-training when he judges the model to be less efficient due to the evolution of the network, the evolution of the customer base and therefore the traffic or other factors influencing overall network performance.

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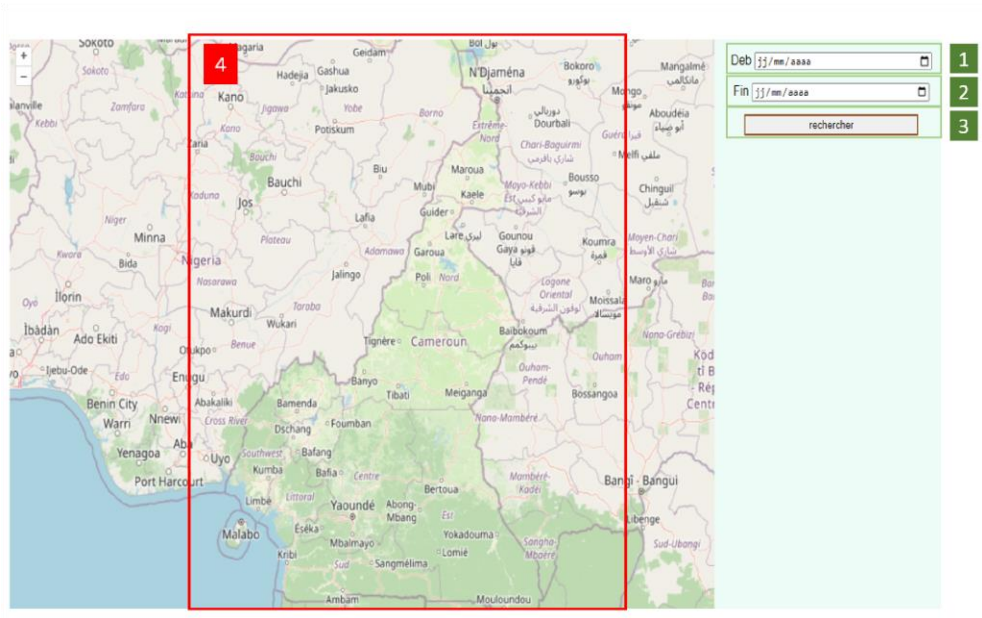

Figure 17. Default satisfaction map by « Model »

Legend:

(1) This button allows you to import the file containing the data necessary to update the inference model

(2) This button allows you to import the file containing the data necessary to update the forecast model

(3) This button Starts the creation of new models.

We therefore have a message validating the creation of the models.

Figure 18 presents the level of customer satisfaction across the national territory.

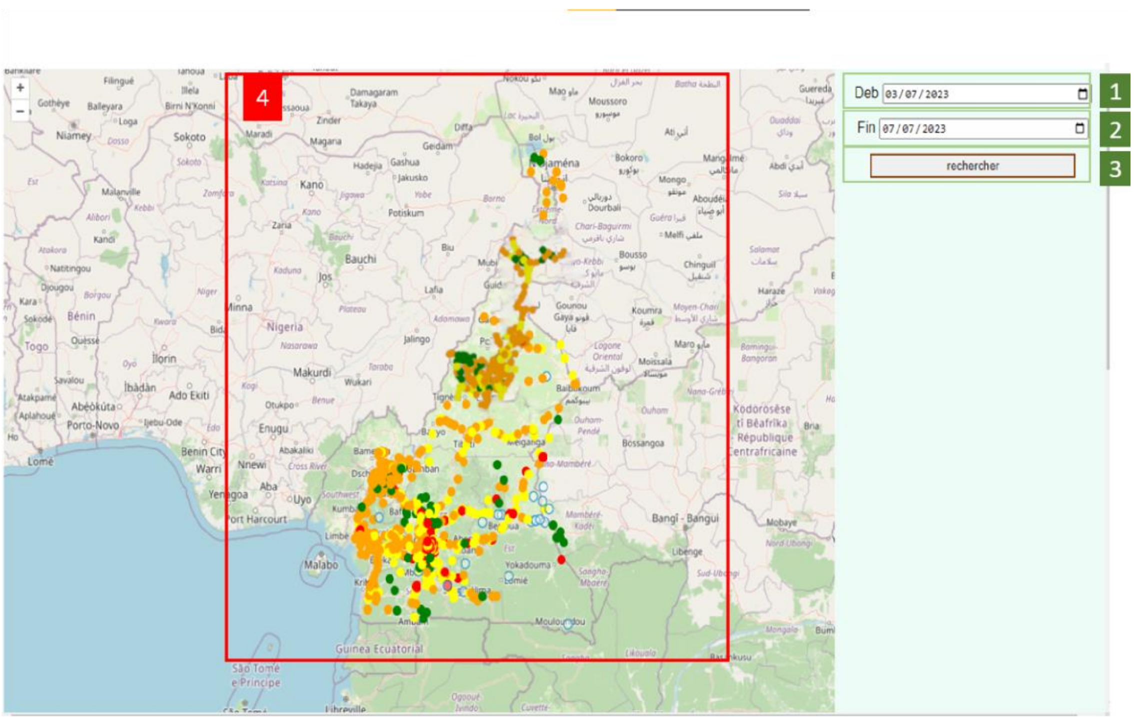

Figure 18. Default satisfaction map

Legend:

(1) This part corresponds to the option allowing you to select the date from which the user would like to make predictions.

(2) This part corresponds to the option allowing you to select the date until which the user would like to make predictions.

(3) We therefore have the search button, which allows us to launch the forecasts and update the satisfaction map.

(4) Satisfaction map of Cameroon with satisfaction levels defined by the clustering model

Figure 19 shows the site on which we want to see the details of the evolution of the performance indicators.

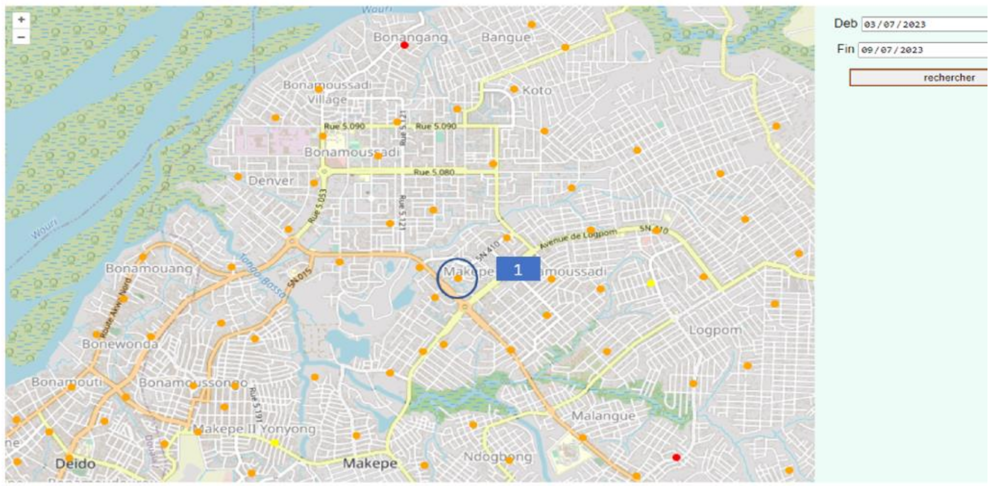

Figure 19. Site selection

Legend:

(1) Site that we select to visualize the evolution of performance indicators.

Figure 20 presents the evolution of the performance indicators on the Site that we have selected

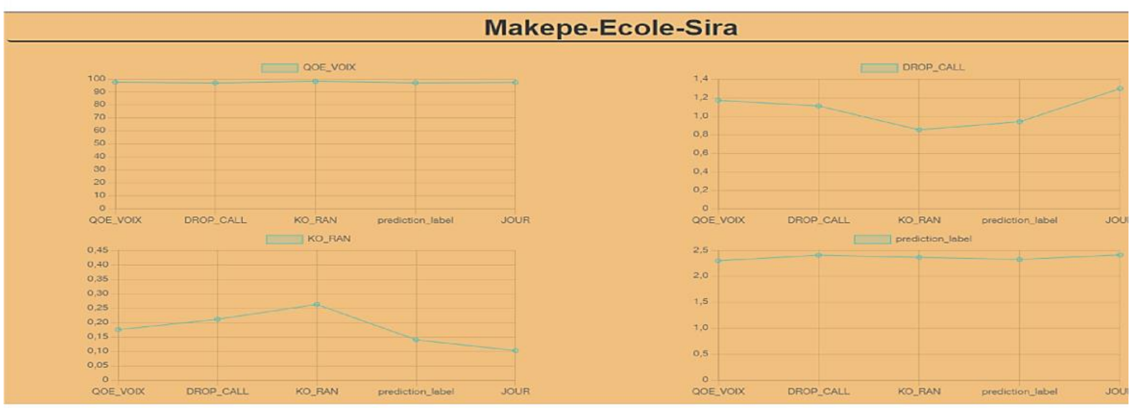

Figure 20. Visualization of the evolution of indicators

5. Conclusion and outlook

This work presented a modeling of the customer experience by Machine Learning using the key performance indicators of mobile technologies with the main objective of the design and development of a tool for predicting customer satisfaction. We obtained a relevant result by setting up the NetPredict solution which allows:

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- -predicting customer satisfaction across the national territory for a specific period.
- -Visualization of the evolution of network performance indicators for a specific future period.
- -Updating the models used by the tool;

As a perspective, we propose:

- Improve the satisfaction survey by extending the sample in order to better understand the network parameters corresponding to each customer satisfaction class.
- Establish a functionality allowing real-time visualization of customer satisfaction levels.
- Enable the detection of customers likely to leave the company or who are detractors

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