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Field of practice: LARIISA: smart digital solutions to support decision-making in Family Health Strategy management

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Abstract *The LARIISA collaborators group has been conducting research and development of technological solutions to support decision-making in health systems since 2009. GISSA, a cloud system resulting from the scientific and technological evolution of the LARIISA project, is among the solutions produced. This paper aims to describe the developing trend of GISSA©, a technological tool supporting the Family Health Strategy in northeastern Brazil, pointing out challenges, paths, and potentialities. This is a descriptive and exploratory study, based on secondary sources from the IBGE, INMET, SINAN, SIM, and SINASC, with quantitative analysis based on machine-learning techniques applied to create digital health microservices. Operating in the northeast and southeast regions, GISSA© provides information that qualifies health managers' decision-making process, improving the municipal health system's management.*
Key words *Digital Health, Health Systems, Family Health Strategy, Information Systems, Mobile Health*

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Introduction

Health management requires decision-making through the best combination of available resources, improving the functioning of organizations, encouraging efficient and practical actions. In Brazil, economic and social crises coupled with demographic, technological, and epidemiological transitions trigger tension for more versatile management forms[1]. In the Unified Health System (SUS), this unfolds in need to implement innovative health policies.

The concept of governance is included in this context, with organized institutional arrangements among different actors, strategies, and procedures to manage, in a shared and inter-federative way, the relationships between operational structures to obtain greater interdependence and better health and economic results[2]. Governance encompasses government institutions and implies non-governmental, informal control mechanisms, which make people and organizations within their area of activity have determined conduct, satisfy needs, and respond to demands[3].

Among the responses to the demands, Health Information Systems (SIS) are essential tools for planning and evaluating health policies and health services, networks, and systems[4]. Concerning these needs, in 2009, the team of researchers from the Laboratory of Intelligent and Integrated Health Networks (LARIISA) developed a project addressing specific requirements of the five classic areas of public health governance: epidemiological clinic, administrative and financial technique, regulations, shared management, and knowledge management[5-7]. This system would be an intelligent digital solution and integrate technologies such as Data Warehouse (DW), ontologies (mashups[8]), and Data Mining (DM)[9,10]. We aimed to modularize a platform that would serve as a basis for building governance intelligence to support decision-making in managing health systems.

The concepts and experiences acquired in the project, then called LARIISA, served as a starting point for the proposal of the GISSA®[11,12] system created to meet the intelligent management of the Family Health Strategy (ESF), the primary strategy of the Ministry of Health (MS) for reorienting health care models, to reorganize PHC practices[13]. Given the many ESF challenges pointed out in the literature[14], such as the low political, economic, and social valorization of the strategy, the low technological density, the fragility of the diagnostic support and clinical information systems, and management issues, attention was drawn to the need to build solutions such as the GISSA® system.

This solution was implemented in 2014 with the following functionalities: generating dashboards, indicators, alerts, reports, semantic search, risk analysis, and inferences based on events monitored by the Live Births Information System (SINASC), Notifiable Diseases Information System (SINAN), Mortality Information System (SIM), PHC System of the Unified Health System (e-SUS AB), National Immunization Program Information System (SIPNI), and the National Registry of Health Facilities (CNES). A proof of concept was implemented in Tauá, Ceará, Brazil, integrating public health strategies in the semi-arid region of Ceará. AVICENA® and Instituto Atlântico® also partnered in this project.

Now evolving through field experiences, in partnership with the digital health startup AVICENA®, the LARIISA group started to develop the GISSA® product and expand its use by prospecting more municipalities for implantation, most of them in the Northeast region. In this process, the digital solution naturally evolved into modules communicating and providing the functions perceived by the user. From this perspective, the components for the acquisition, handling, and visualization of data were integrated, and ontology, artificial intelligence, and, more recently, chatbot services were coupled with the platform for health governance.

Based on these elements, this paper aims to describe the evolution of GISSA®, a technological tool that supports the Family Health Strategy in northeastern Brazil, pointing out challenges, paths, and potentialities. We were unable to find any publication exemplifying a national or international study of a similar system for comparison purposes due to the specific governance nature of the Brazilian public health system and the application niche of the research described in this paper.

Methods

This is a quantitative, descriptive, and exploratory study with secondary sources from governmental systems such as the Brazilian Institute of Geography and Statistics (IBGE), the National Meteorological Institute (INMET), and national health information systems such as SINASC, SIM, and SINAN.

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The implementation of the software system followed SCRUM[15], a swift and incremental development methodology based on the concept of sprints, subdivisions of the project period in intervals. This technique foresees three actors in the process of developing the system. The product owner is responsible for improving the value proposition to be delivered by the product; the Development Team, composed of professionals who do the work to deliver versions with incremental improvements for each sprint; and scrum master, a technician with experience in developing responsible for coordinating solutions to the demands presented to the Development Team and the product owner, ensuring that the team follows the SCRUM practices and rules.

The method requires three meetings to discuss the project's aspects to facilitate communication: the daily meeting (daily), which certifies what was done the day before, identifying what prevents the team parts from moving forward, with allocation/sorting of the remaining activities; the review meeting, held at the end of the sprint to present the implemented features; and the retrospective meeting, to review the mistakes and achievements of the last sprint to promote team learning.

The work included two municipalities in the state of Ceará, Brazil. The first was located in the region of the Inhamuns backlands and categorized as the second-largest municipality in the state in the territorial surface area: Tauá. The second, the capital of Ceará, located in the northeast of the country: Fortaleza. A proof of concept was implemented in Tauá, integrating public health strategies in the semi-arid region of Ceará. In Fortaleza, a mock-up (prototype) of the weekly epidemiological chart for Dengue was presented, showing the estimate made in the 25th week of 2020.

The study is based on the description of the composition of two classes of artificial intelligence microservices: risk analysis and prediction of indicators, to identify and present their challenges and potential. The risk analysis is calculated for maternal and newborn/child health. On the other hand, the prediction of indicators focuses on epidemiological surveillance and, more specifically, on knowledge about the set of health determining and conditioning factors related to arboviruses to recommend measures for the prevention and control of Dengue.

Data from SISNAC and SIM from the municipalities of Caucaia, Quixeramobim, Quixeré, Arneiroz, Pacatuba, Sobral, and Tauá from 2007 to 2018 were targeted concerning the risk analysis concerning maternal and neonatal/child health, enabling the construction of machine learning models that identify varying degrees of risk to the health of these groups, qualifying the decision-making of health managers. Similarly, data from IBGE, INMET, and SINAN available for Fortaleza, Caucaia, Quixeramobim, Pacatuba, Sobral, and Tauá, collected from 2007 to 2019 and applied to the machine-learning models developed were used. We can predict the number of individuals infected with Dengue to be confirmed by SINAN in the next few weeks in a given location based on data from these three sources.

The quantitative analysis of these data was performed with the machine-learning models developed by LARIISA shown below. The study was submitted to the Research Ethics Committee of the School of Public Health of Ceará (ESP/CE) through Plataforma Brasil, and was approved.

Results and Discussions

Many public or private entities and independent researchers can develop health intelligence services with access to data in different fields of analysis. From images to information showing contact between people (contact tracing), teams can analyze this microdata by creating specific models in response to operational demands. Based on the REST technology, the GISSA® intelligence module has inference services for maternal and child death risk and models for epidemiological surveillance applicable to arboviruses.

Digital Health Systems architecture

Digital health or the digital technologies used for health have become an essential field of practice by employing routine and innovative forms of Information and Communication Technology (ICT) to meet health needs. The term digital health is rooted in eHealth, defined as "the use of information and communication technology in support of health and health services". Mobile Health (mHealth) is a subset of eHealth and is defined as "the use of wireless mobile devices for health". Within this context, the term digital health was introduced as "a broad umbrella that encompasses eHealth and emerging areas, such as the use of advanced sciences in "Big Data", genomics, and artificial intelligence[16].

In this study, we approach the composition of two artificial intelligence microservices, which are part of the GISSA® system, born from a solution for public health governance in primary care and a growing evolution process. It emerges as a tool to support decision-making based on information extracted from the national health information systems SINASC, SIM, SINAN, e-SUS, SIPNI, and CNES; including other government systems, such as IBGE, INMET, and the State Audit Court (TCE). In the works described here, the data are extracted from municipal databases and web systems of interest (Figure 1). They are aggregated and structured in helpful information for the family health and municipal management team, supporting public policies. The services of ontology, artificial intelligence, and, more recently, chatbots comprise three distinct blocks that cooperate with the system providing specific functions via consultation.

Data source is at the base of 4.0 health systems. Each system that provides information about the individual (microdata) is considered a micro-source. There are countless examples in health, from electronic bracelets (smartbands) to reverse-transcriptase polymerase chain reaction (RT-PCR) processing machines used for viral detection tests, producing vast amounts of data every day. In their generation, this microdata is qualified and, with the individual's consent, recorded at the next level of architecture, under the control of the responsible institution, whether health authorities or specialized companies (hospitals, health plans, and startups). The algorithms manipulating the microdata to translate it into useful information are found in the service layer. For example, in this approach, a microservice would aggregate COVID-19 cases registered in 2020 in Fortaleza in an intermediate table. Another would use this result to present the chart of cases per epidemiological week to the health management team in the application layer.

Figure 2 presents the architecture of health systems considering the structure of microservices, identifying artificial intelligence microservices as a subset of the services implemented in this layer.

In this sense, at the end of 2019, the National Health Information and Informatics Policy (PNIIS), promoted by the Ministry of Health through the SUS Informatics Department (DATASUS), proposed the National Health Data Network (RNDS)[17]. This initiative allows different public/private partners to cooperate with the RNDS, which would allow information related to the citizen's health to circulate freely among the professionals involved in the care, promoting efficiency in patient monitoring, essential in the

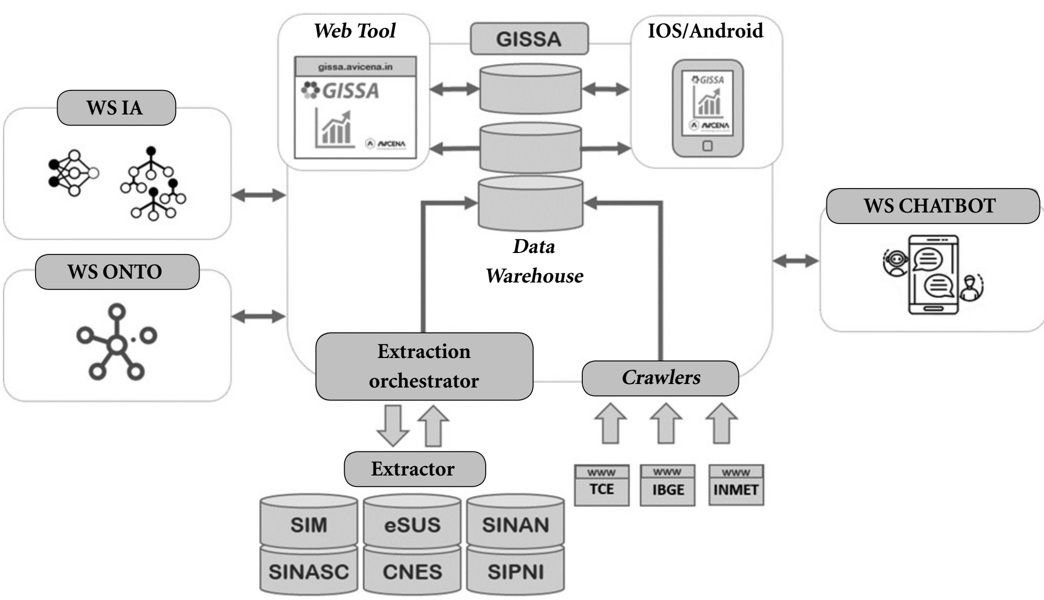

Figure 1. Components of the current system architecture.

Source: Elaborated by the author.

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development of systems that can build the user's pilgrimage in the various lines of care accessing different SUS care networks.

Currently, the GISSA® system is experiencing the aggregation of new functions, following an architecture of greater granularity with the proposal of health microservices. In this paradigm of building digital systems, a set of atomic services are designed with Representational State Transfer (REST) technology, promoting a stable implementation environment and the development of scalable applications. In other words, it serves a user with the same quality that serves millions around the globe.

A subset of these microservices is artificial intelligence models. These algorithms evaluate microdata, enabling new analyses about the health of an individual or population. The services currently available in the intelligence module are the analysis of maternal risk, neonatal/child risk, and, more recently, the detection of epidemics produced by Dengue arbovirus, projecting the number of cases weeks in advance to be confirmed by SINAN.

Inference of maternal and neonatal/infant risk

The collection of microdata both by SINASC, when the birth of a child occurs, and by SIM, in the event of death, allows training algorithms to identify the risk of death. Mother (pregnant woman or puerperae) and child (newborn or infant) are assisted with different pattern recognition models applied at different stages of pregnancy and child development, identifying and providing better follow-up for those more complicated cases. Also, aggregating this individualized information allows the public or private health system manager to measure the necessary care structure at different competence levels (municipal, state, or federal) or scales.

The academic results[18-20] show that it is possible to identify the risk of maternal death with part of the information already collected by SINASC with more than 90% accuracy from a set of features collected by the live birth and death declaration forms. LARIISA collaborators cross-referenced the data collected in the

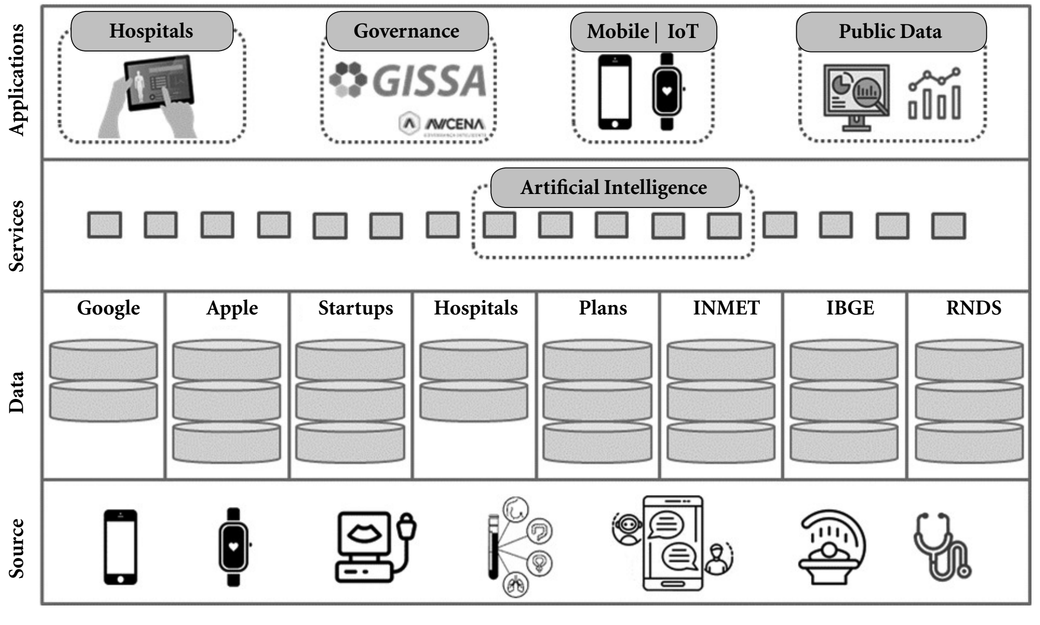

Figure 2. Architecture of health systems following the use of microservices.

Source: Elaborated by the author.

information systems of interest to the research municipalities from January 2007 to December 2018, creating two different datasets, considering each application context (maternal and neonatal/child). Each sample corresponds to the set of mother and child characteristics, divided into two classifications: live and deceased (Table 1). The datasets served as input for the training of machine-learning models such as the Gaussian Naive Bayes[21] (GNB), Random Forest[22] (RF), and Decision Tree[23] (DT), which calculate the probability of a given individual belonging to the death risk group. The evaluation of the performance of the classification algorithms included the application of the K-fold Cross-Validation technique (k=10). From the analysis of the results obtained, we observed that the algorithms achieve results that agree with each other, and the RF obtained greater accuracy among the evaluated models, probably due to the characteristic of this Ensemble Learning algorithm in combining multiple decision trees to decrease variance and overfitting, when the model adapts to the data used in training, incorrectly classifying new samples.

Figure 3 shows the Receiver Operating Curve (ROC) for the maternal risk model that uses 18 characteristics – 97.4% accuracy – (e.g., place of birth, mother's education, child's ethnicity, and gender) and for the child model with 27 characteristics – 93.9% accuracy – (e.g., father's age, mother's age, maternal education, and maternal marital status)[18].

The intelligence module uses supervised machine-learning classifiers to calculate the risk of maternal and child death. A total of 27 predictive models for neonatal/infant death risk and 18 models for maternal death risk are generated considering scenarios where subsets of characteristics are available for risk assessment. Figure 3 shows the estimated risk for the population served by the public health system in Tauá, calculated based on the risk analysis models of the GISSA® system. The predictive models selected for each risk classification setting (maternal and neonatal/infant) are serialized and remain available in a cloud REST Application Programming Interface (API).

Table 1. Samples for maternal and child risk analysis.

Dataset	Live	Deceased	Total
Maternal	2,531	508	3,039
Child (0-365 Days)	657	682	1,339
Neonatal (0-28 Days)	911	952	1,863

Source: SINASC and SIM, elaborated by the authors.

According to Canuto[24], the GISSA® system used by Tauá had a visible impact on the work dynamics, emphasizing: agreeing indicators with qualified data; shared access, facilitating communication; decision-making, and shared responsibility in health production with solution functionality, especially alerts and reports, contributing to the construction of a health planning, monitoring, and evaluation culture, which corroborates the potential of the studied cloud system.

The primary potentialities also include the political will and technical understanding of the manager and the team that received the system; competitive professionals who participated in the development and implementation process who continue in the municipal management; the construction of the project based on the needs of the municipality and with the participation of local technicians; delivery of smartphones to health professionals and people in the community, providing tools and encouraging the use of the solution; support, promotion of training and permanent support of the local coordination and consultant at the central level of the project; articulation of GISSA® with the Primary Health Care Planning Project[25], which preceded it in Tauá, with professional qualification of the entire health workforce at the PHC level, while qualifying the Health System and the Information System; PHC units chosen for the proof of concept with accumulation of successful experiences, considered "laboratory units" in the Planning Project and other initiatives; community involvement in prevention and health promotion, with the selection of pregnant women and mothers of children under 2 years of age to participate in the project.

The challenges were also highlighted, such as the alternation of political power, with visible signs of partial commitment to the continued development of the GISSA® project; the replacement of nursing professionals (coordinators) in the PHC units, including the proof-of-concept units, with recruits remaining, with also unstable contractual bonds; technicians' turnover; technical failures regarding the lack of internet signal and the functioning of GISSA® robots to capture information from health systems, compromising their use and discouraging teams; a significant number of professionals with limited knowledge of digital technology, which leads us to reflect on

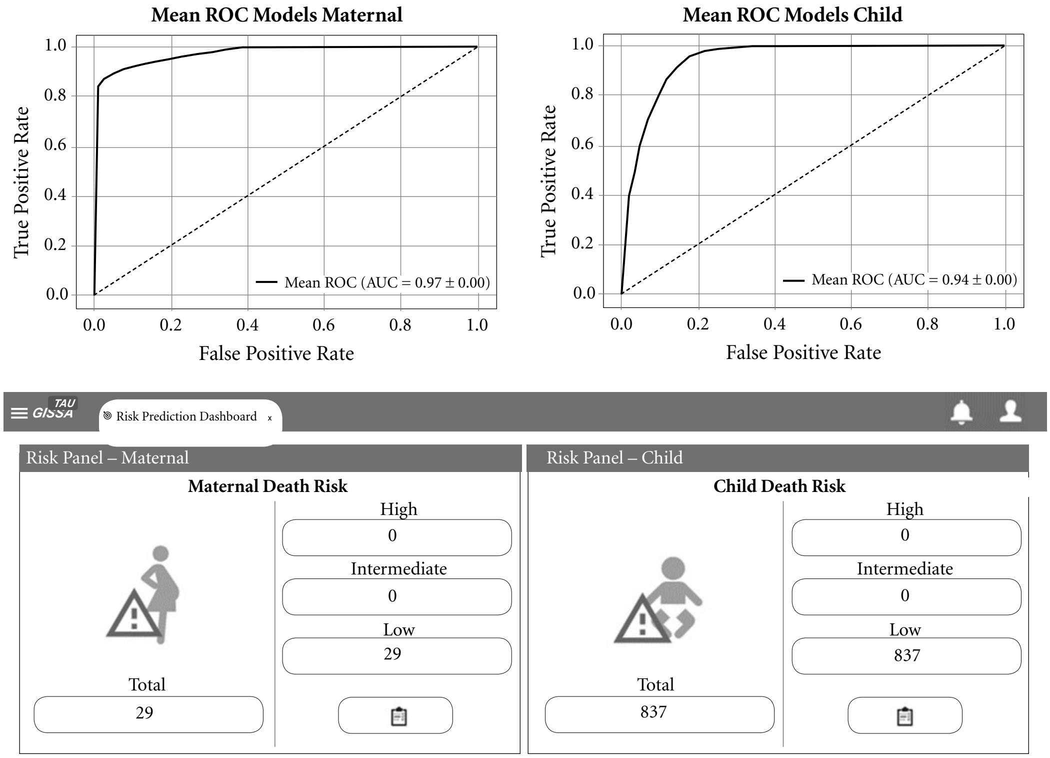

Figure 3. Mean Receiver Operating Curve for the GISSA® Prediction and Screen models for the risk monitoring of mothers and children accessed in August 2020.

Source: GISSA® (https://gissa.avicena.in/)

the importance of digital literacy[26] of health professionals as well.

Epidemiological surveillance

Legislation[27] defines epidemiological surveillance as a set of actions that provide knowledge, detection, or prevention of any change in the determining and conditioning factors of the individual or collective health to recommend and adopt measures to prevent and control problems or diseases.

In the context of this study, a contribution is made to a set of actions that provide knowledge about determinant and health conditioning factors concerning arboviruses. In a country with continental dimensions like Brazil, with very different climates such as the semi-arid and the tropical, arboviruses (Dengue, Zika, Chikungunya, and Yellow Fever) are endemic diseases in some locations, with a minimum plateau of cases per year, and depending on the conditions, may evolve to an epidemic[28].

Northeastern Brazil has suffered mainly from cases of Dengue, the most popular form of circulating arbovirus in this region. Because they are correlated diseases and dependent on the transmitting mosquito with the potential for significant epidemics, the Ministry of Health monitors the proliferation of mosquitoes in urban areas through the Rapid Index Survey for Aedes Aegypti (LIRAa)[29]. Another critical tool in combating arboviruses is SINAN, which provides microdata for monitoring infected people.

The idea is that the curve of accumulated infection cases follows the logistic or sigmoid mathematical function, with the number of cases per week obtained by the derivative function[30]. The viral spread is observed in four well-defined phases in the event of epidemic potential: (I) exponential growth in the number of infected, (II) rapid decline in the rate of new cases, (III) inversion in the rate of new cases, and (IV) exponential decrease in the number of new cases. As it is a stochastic process, we naturally relate several factors related to the arbovirus epidemics, especially meteorological measures directly influencing the proliferation of the disease vector: the mosquito[31,32]. Aggregate population, meteorological, and infection measures are subsidies for a set of Artificial Neural Networks (ANNs) to predict the number of infected individuals that will be observed in subsequent weeks, which allows recommending and adopting measures for the prevention and control of arbovirus-related diseases or problems.

The arbovirus-related information is maintained and made available by INMET[33], IBGE[34], and SINAN[35], all of which are part of the information structure of the Brazilian federal government. Among other duties, INMET is responsible for maintaining and collecting meteorological information from bases spread throughout the national territory. IBGE maintains and updates the characterization of the population in each region, and SINAN collects and makes available the number of infected people by region through the monitoring of notifiable cases.

Data were collected from cities of Ceará; namely, Fortaleza, Caucaia, Quixeramobim, Pacatuba, Sobral, and Tauá to create the microservice to predict the number of dengue cases to be confirmed in the coming weeks. Sixty-five events were observed between outbreaks and epidemics distributed in 27,895 samples divided into two groups, with 9,445 atypical days (with five or more confirmed infection records) and 18,450 typical days (less than five cases). Measurements were taken daily between January 2007 and December 2019. Data were added for each daily sample: moving average of the number of infected by Dengue; accumulated rain precipitation (mm); accumulated evaporation (mm); moving average for daily maximum, mean, and minimum temperatures; daily heat stroke moving average (hours); wind speed moving average (m/s); population and demographic density. All moving averages and accumulations consider the measurements collected in the last seven days from the date of the sample.

Considering outbreaks or epidemics with a minimum duration of 7 weeks and a maximum duration of 60 weeks and given the mean duration of the events of 30 weeks, we chose to generate ten models to predict the number of infected in the coming weeks 1, 2, 3, 4, 5, 6, 7, 8, 9, and 10. The trade-off between accuracy and predictability in the coming weeks is apparent during the data mining process. The prediction models lose accuracy as the number of infected people's behavior is predicted more weeks in advance. Predicting the incidence of the following week, we observed a Mean Absolute Error (MAE) of 3.18, 4.07 (5th week), and 5.62 (10th week) infected by forecast.

Another observed aspect is that prediction reduces sensitivity. In other words, it loses the ability to predict small events (below 60 weekly cases) insofar as data from cities with different population quantities are used. Samples of infection events in Fortaleza (2.7 million inhabitants) are quickly much more significant than those in Caucaia (361 thousand), Sobral (210 thousand), Pacatuba (83 thousand) or Tauá (59 thousand)[17]. The results for Week 1 (after the measurement day) show MAE of 20.35 infected per prediction, 31.02 (5th week), and 45.39 (10th week). Thus, two models are proposed: small cities have less than 150 thousand inhabitants, and large cities stand above this mark.

Taking an epidemic that occurred in 2008 in Fortaleza, Figure 4 shows the predictive trend from the 4th week. Additionally, it presents Dengue's epidemiological surveillance service's conceptual screen applied to Fortaleza given the 2020 measurements. The forecast in the 25th week points to a growing number of cases in subsequent weeks, showing the trend of local outbreaks or even an epidemic peak in the 34th epidemiological week.

The experiments show that extending the prediction to more than ten weeks causes instability and, possibly, event shading, that is two epidemics of different sizes occurring with close infection peaks. This behavior is mitigated by reducing the number of infection incidence predictions by epidemic phase: 10 weeks in advance for phases I, II, and IV; and five weeks in advance for phase III.

It is noteworthy that more experiments are required to assess the sensitivity of the prediction for regions other than those where the model was designed and that this technique can be quickly adapted to other events of arboviruses such as Chikungunya fever, Yellow Fever, and Zika, as they depend on of the same vector. Additionally, mathematical modeling can be adapted to any epidemic (tuberculosis, cholera, COVID-19, etc.) just by choosing variables that correlate with the conditions of the presence of the virus in circulation and contamination.

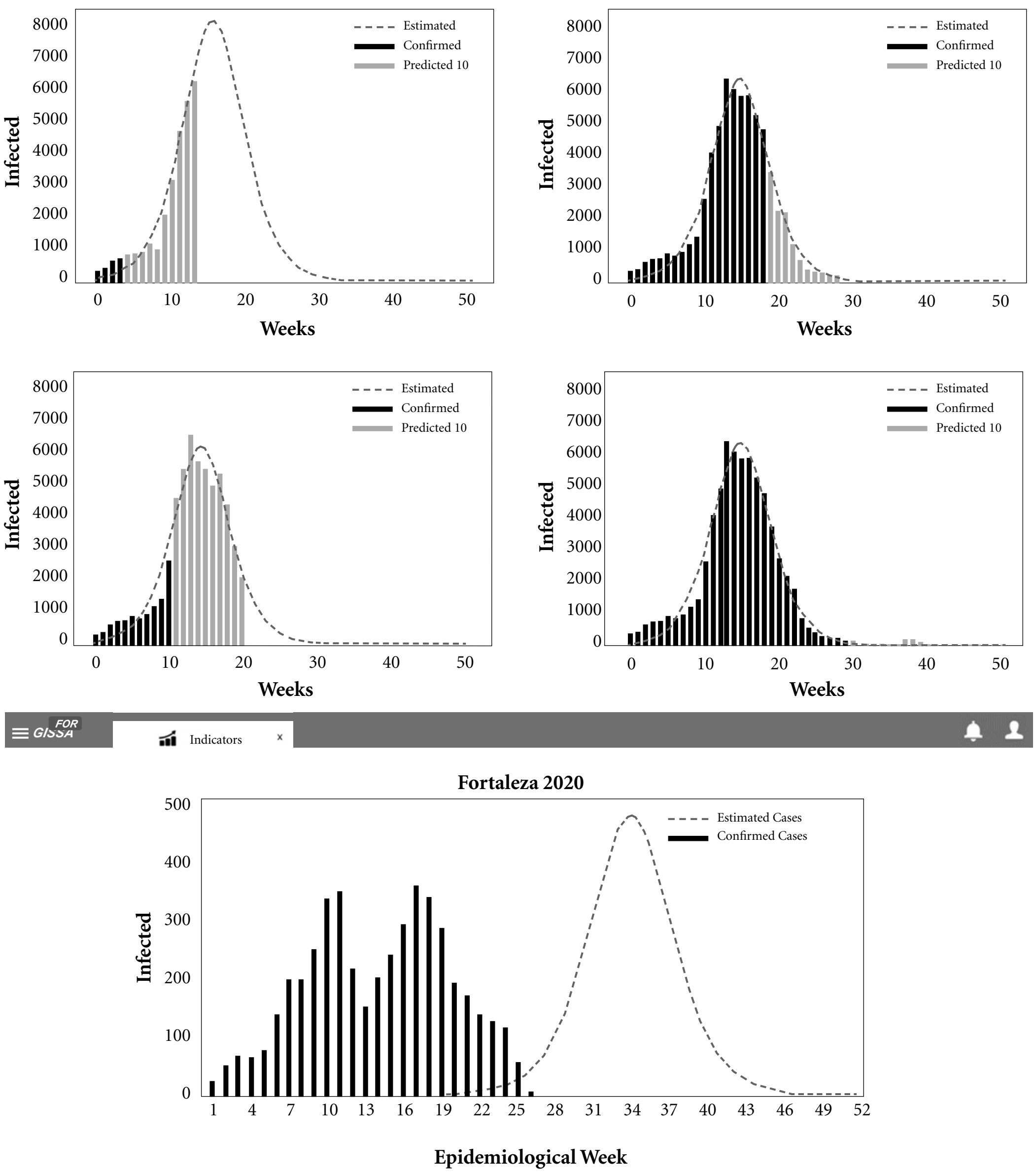

Figure 4. Trend of the estimated epidemic in the city of Fortaleza in 2008 and proof of concept applied to the same municipality in the 25th week of 2020.

Source: Elaborated by the author.

Final Considerations

GISSA® is a commercial product resulting from the scientific and technological evolution of the LARIISA project. It is currently operated in Brazil in the Northeast and Southeast regions as a cloud system providing qualified information in managing the municipal health system. This contextualized information qualifies the decision-making process of health managers at the municipal level.

Besides data originating from the Brazilian government's health systems, the system collects different sources of data for context detection and application of artificial intelligence techniques.

GISSA® has an expanded view of public health management, considering everything from epidemiological to financial/regulatory aspects.

The modularization of GISSA® allows the use of developed intelligence microservices by different partners. Different systems will consult the GISSA® cognitive server in this setting, which responds instantly about risk analysis and indicator prediction. However, other applications handling a larger volume of data and requiring less response time demand faster communication speed, a horizon that opens up with the promising 5G connection. Another challenge for the popularization of artificial intelligence techniques applied in digital health is the standardization in the representation of information (images, medical protocols, the designation of diseases, immunization, etc.). Despite what has already been accomplished, there is still a long way to ensure interoperability between futuristic systems and settings that can be confirmed for users of healthcare systems. The use of relevant, intelligent systems similar to GISSA® for the local or regional health system's governance is not yet widespread in Brazil, considering specific requirements of five classic governance areas.

From the creation of the LARIISA Project in 2009 to the GISSA® product, already commercially available and in operation in several Brazilian municipalities, it is essential to highlight the rich academic trajectory developed in line with the project, totaling two dozen theses and dissertations, more than forty scientific papers published in several international events, and many prototypes and software records, which motivates the team to continue researching and developing inputs to improve the management of health systems.

Collaborations

RV Costa Filho, KG Ribeiro, SSL Pereira, DB Andrade, and LLS Ribeiro contributed to elaborating the manuscript design – introduction, architecture for digital health systems, artificial intelligence microservices, and final considerations. AMB Oliveira and JN Souza contributed to the critical review of the first version of the manuscript. LOM Andrade and J-L Dennis collaborated with the final reading and critical review of the paper. All authors have approved the final version and are responsible for all aspects of this work, including ensuring accuracy and integrity.

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