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ARTIFICIAL INTELLIGENCE MODEL IN BODY SCAN IMAGES FOR MONITORING TUBERCULOSIS IN A PRISON COMPLEX

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Abstract: Tuberculosis (TB) remains a significant public health challenge worldwide, with its transmission exacerbated by various risk factors including co-existing health conditions and socio-economic determinants such as high population density, poverty, and alcoholism. This study emphasizes the crucial role of efficient TB screening and monitoring in not only providing prompt treatment to patients but also in reducing the disease's lethality. Responding to the Ministry of Health and the World Health Organization's demand for advanced diagnostic methods, we introduce a novel approach using the Marie. AI model for TB screening in penitentiary complexes. This proof of value (POV) repurposes Body Scan images, typically used for object detection on inmates, as a new tool for health screening.

The Marie.AI model, a multimodal artificial intelligence platform developed in 2020, has previously proven effective in Brazil for aiding healthcare teams in diagnosing COVID-19 and TB. For this study, the model was trained on an extensive dataset of 1.5 million images, including X-rays and CT scans of patients with TB, COVID-19, and other pulmonary diseases, along with patient symptom data. A significant achievement of this study was the model's ability to distinguish between TB-infected and non-infected individuals using Body Scan images, leveraging its previous training with X-ray and CT data. The model demonstrated exceptional diagnostic accuracy, achieving a specificity of 87.23% and a sensitivity of 100% in identifying suspected TB cases. These findings not only highlight the versatility of the Marie.AI model in non-traditional settings but also mark a breakthrough in early TB diagnosis, particularly in high-risk environments like penitentiary complexes. This innovative approach promises to enhance public health responses to TB, leading to more effective disease management and control.

INTRODUCTION

The World Health Organization (WHO) Global Tuberculosis Report 2022[1] provided provisional estimates of global tuberculosis (TB) mortality in the year 2021, attributing the observed increase to disruptions in health services caused by the COVID-19 pandemic. This period saw the implementation of various government measures aimed at curbing the spread of COVID-19, including school closures, travel bans, restrictions on public gatherings, as well as mandatory mask-wearing and hand hygiene practices[2]. The clinical manifestations of COVID-19 closely resemble those of other respiratory infections, notably pulmonary tuberculosis (TB)[3]. While TB is a significant global health concern, it is also a curable disease with both affordable treatment and prevention options available. Despite this, TB remains one of the leading causes of death globally from a single infectious agent, akin to the mortality impact of COVID-19[2].

An examination of national monthly and quarterly TB reports was conducted to identify interruptions in essential TB services during the COVID-19 pandemic at the national level. This analysis aimed to understand the impacts on both the supply side (the ability of health systems to continue providing services) and the demand side (public access to health facilities and treatments). The findings revealed that the COVID-19 pandemic significantly affected the provision of TB health services in various countries. This was evidenced by the reallocation of healthcare professionals, alterations in healthcare budgets, and interruptions in services[1]. Notably, in Brazil, the year 2021 saw a report of 68,271 new TB cases, which translates to an incidence rate of 32.0 cases per 100,000 inhabitants (figure 1). This statistic underlines the significant impact of the COVID-19 pandemic on TB management and control efforts in Brazil.

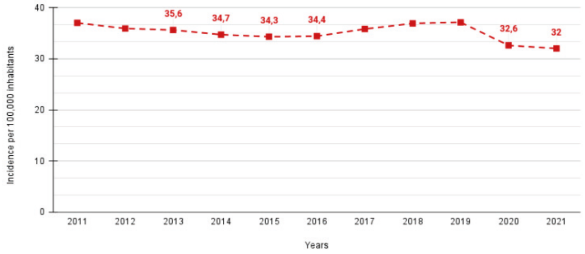

Figure 1. Coefficient of incidence of general tuberculosis (per 100 thousand inhabit.)

In 2020, Brazil and 15 other countries were responsible for a 93% reduction in TB notification worldwide. This negative variation can be justified by the impacts caused by the COVID-19 pandemic on health services and systems[4]. Later, measures to remove tuberculosis became increasingly unlikely, as during this period, there was a 25% decrease in diagnosis and a 26% increase in TB deaths worldwide. In this context, faced with the need to expand and qualify care, surveillance, and management actions for TB control in the country, the General Coordination of Surveillance of Chronic Communicable Respiratory Diseases (CCRD) of the Ministry of Health, published in 2021, is a guiding document for the second phase of the National Plan to end TB as a public health problem. With recommendations for the period 2021-2025, the Plan has goals in line with commitments from international organizations, such as the 2030 Agenda of the Sustainable Development Goals, and aims to reduce the incidence of TB to less than 10 cases per 100,000 inhabitants and less than 230 deaths. until 2035 (BRAZIL, 2021). The diagnosis of tuberculosis during COVID-19 shows a drop in vulnerable populations, such as prisoners. When stratifying the frequency of TB cases by type of vulnerable population and considering the period from 2015 to 2021, there was a variation from 5,860 to 6,773 TB cases in a population deprived of liberty[1]. The prevention and control of TB, especially in the prison environment, should be reinforced by the diagnosis of TB, which is carried out through clinical evaluation and the request for imaging exams and collection of biological material for identification. However, to intensify the search. Process in this environment, the Ministry of Health[1], proposed passive search and activation of TB cases among prisoners, according to the flowchart below (Figure 2):

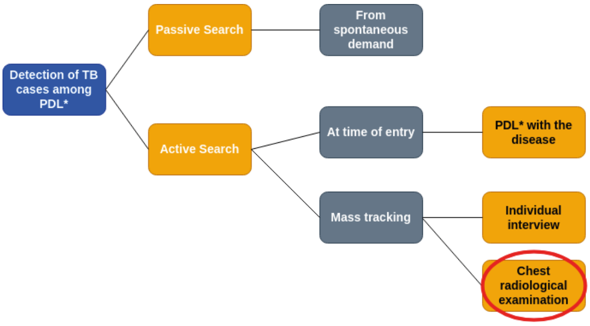

Figure 2. Flowchart for screening and diagnosis of TB; *Population Deprived of Liberty (PDL)

The effective screening of individuals presenting with respiratory complaints to health services is crucial for the accurate and timely diagnosis of tuberculosis (TB), as well as other medical conditions. However, it is observed that not every patient exhibiting symptoms indicative of TB receives appropriate treatment or even a definitive diagnosis of the condition. This issue is particularly pronounced in prison complexes[5], where TB screening remains suboptimal.

Within the context of Brazil's prison complexes, the healthcare infrastructure typically includes a team comprising a nurse and a doctor. Despite this professional healthcare presence, there is a notable lack of essential diagnostic equipment, such as imaging and laboratory testing apparatus. This deficiency significantly hinders the ability to conduct thorough screenings and accurate diagnoses of TB among the incarcerated population. The absence of these vital diagnostic tools underscores a critical gap in the healthcare provision within these settings, potentially leading to delayed or missed diagnoses of TB, thereby exacerbating the health risks not only to the individual prisoners but also to the wider prison community.

Despite the efforts made, the situation remains concerning in environments where overcrowding is prevalent. Public Health Security data indicate that approximately 40% of Brazilian prisons lack medical offices, and 48% are devoid of a pharmacy or a designated area for storing medications[6]. This shortfall in healthcare infrastructure contributes to Brazil having one of the highest tuberculosis (TB) mortality rates in its penitentiary complexes, with a staggering 1,403 cases of TB per 100,000 incarcerated individuals. In stark contrast, the incidence of TB in the general population is significantly lower, at 40 cases per 100,000 people. This disparity highlights the vulnerability and health risks faced by the prison population, in what is the world's third-largest prison system. The high rate of TB in these settings can be attributed to insufficient infrastructure for healthcare teams, overcrowding, and inadequate hygiene conditions[1]. These factors combine to create an environment where infectious diseases like TB can spread more easily, underscoring the urgent need for improved health services and conditions in Brazilian penitentiaries. (figure 3).

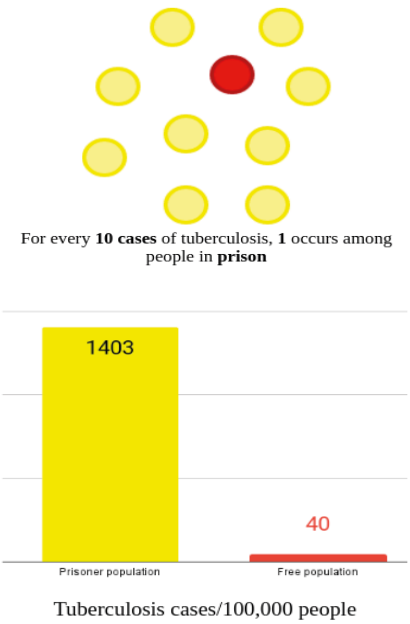

Figure 3. Data on the prison population in Brazil

These failures result in missed opportunities for early TB detection and increased disease severity, leading to more significant complications and the risk of poor outcomes for TB patients. The current situation results in a heightened burden of disease within the community, primarily due to an increased risk of transmission of Mycobacterium tuberculosis. This risk is exacerbated by the insufficient availability of diagnostic materials and technologies for tuberculosis (TB) in prison complexes. Consequently, this deficiency prompts various groups to focus on developing applications in the field of Public Health, aimed at addressing these critical gaps. The development of these applications is essential for improving TB diagnosis and management in these high-risk settings, ultimately contributing to better health outcomes both within the prison system and in the broader community.

An additional noteworthy aspect is that, during the pandemic, the general Brazilian population exhibited a decline in data related to notifications and underreporting of tuberculosis, falling below the levels observed in previous years. This trend indicates a significant disruption in disease reporting and tracking during the pandemic period, underscoring the impact of COVID-19 on public health surveillance systems (Figure 4).

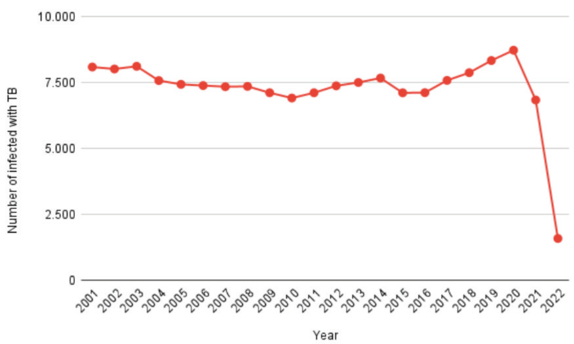

Figure 4. Number of TB notifications from 2001-2022 in January

In the Americas, more than 70 people die from tuberculosis daily, and about 800 become ill with this disease. In 2020, there were an estimated 18,300 children with TB in the Americas, half under five. Efforts in the Region to combat tuberculosis have saved around 1,270,000 people since 2000. The incidence of tuberculosis in Brazil was 45 cases per 100,000 people in 2020, down from 46 cases per 100,000 people in the previous year. This is a change of 2.17%. Due to the high incidence and a low number of notifications and adherence to TB treatment during the pandemic period, we used an artificial intelligence approach as a proof of concept to identify TB in prison complexes as a measure to promote the National Tuberculosis Surveillance System in Brazil[9], given the need to investigate in more detail the characteristics of TB in prison complexes, with a view to a National Project for the Elimination of Tuberculosis in prison complexes[4].

Consequently, this research proposes the utilization of Body Scan images for tuberculosis (TB) screening in prison environments[7]. The study is designed as a proof of concept, aiming to assess the feasibility of using Body Scan technology, commonly employed in Brazilian prison complexes for detecting objects like cell phones and drugs, as a potential tool for TB screening via artificial intelligence. It is important to note that the MARIE.AI[8,18] platform, which is under consideration for this purpose, was originally trained only with X-ray and CT images. This distinction is critical, as X-rays are high-energy, short-wavelength waves capable of penetrating the human body, while body scanners operate using radiofrequency waves, which are of lower energy and longer wavelength, and are reflected off the body. Thus, this proof of concept study is intended to explore new possibilities in the application of pre-trained models and their ability to segment and extract pathological features from different types of imaging, potentially broadening the scope of TB screening methods in challenging settings like prisons.

METHODS

The set of images was acquired from the body image file, model Spectrum BodySca Dual View, serial number 1203000002, used in security procedures at the Chapecó Agricultural Penitentiary. The study was approved by the Ethics Committee for Research on Human Beings of Santa Catarina State University, number 4874132. All subjects gave their informed consent for inclusion before participating in the study. The study was performed in accordance with the Declaration of Helsinki.

In this project, historical Body Scan images from two distinct patient groups were utilized: one group comprised individuals diagnosed with tuberculosis (TB), and the other included patients without any respiratory disease complaints. These images were selected from well-defined case studies.

It is pertinent to note that all patients involved had their diagnoses of either Tuberculosis or COVID-19 medically confirmed (Figure 5).

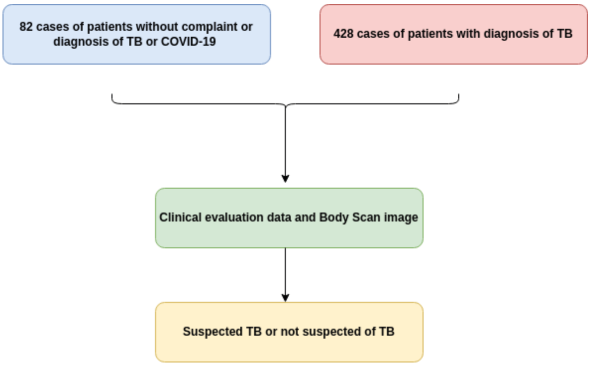

Figure 5. Data on the prison population in Brazil

VARIETIES OF IMAGING MODALITIES AND THEIR PHYSICAL CHARACTERISTICS

Body Scan imaging typically employs millimeter wave technology or backscatter X-ray systems, predominantly utilized in security settings such as airports and prisons. These systems are designed to detect objects concealed on or under an individual's clothing. The resultant images are two-dimensional, effectively delineating the contour of the person's body and any objects present. However, unlike medical imaging techniques, Body Scan images do not provide internal anatomical details.

In terms of physical properties, Body Scans utilize non-ionizing radiofrequency waves in millimeter wave scanners, or low-dose X-rays in backscatter systems. These technologies are characterized by significantly lower energy levels compared to those used in medical X-rays and Computed Tomography (CT) scans. Their design principle is based on the reflection of these waves off bodily tissues and other objects, rather than penetrating them as in medical imaging.

Consequently, the radiation exposure from Body Scan systems is considerably lower than that from medical X-rays and CT scans. Specifically, millimeter wave scanners employ non-ionizing radiation, which is generally deemed safer for human exposure, further reducing the associated health risks commonly linked with ionizing radiation.

MARIE.AI PLATFORM

Marie.AI[8,9,10], a sophisticated multimodal artificial intelligence model, has been developed with the primary aim of facilitating the diagnosis of various lung diseases. In August 2020, this model was employed in specific municipalities[9,10] to bolster the efforts of health teams in monitoring and addressing Tuberculosis, COVID-19, and pneumonia.

Over a span of three years, Marie.AI[8,9,10] has been operational within the Brazilian healthcare system. At this juncture, we have undertaken a detailed, case-by-case evaluation of the platform in collaboration with healthcare professionals. The evaluation process was grounded on two principal metrics: (i) Sensitivity, which is concerned with the model's accuracy in identifying confirmed positive cases of Tuberculosis (true positives), where confirmation was obtained through AFB testing and medical diagnosis; (ii) Specificity, which gauges the model's precision in correctly identifying individuals who are not suffering from the disease being tested.

These metrics play a pivotal role in ascertaining the model's capability to accurately detect the presence or absence of the disease, especially in instances where an individual exhibits signs or symptoms of TB that correspond with the characteristics identified in the image.

Additionally, the synthesis of diagnostic test outcomes leads to the calculation of an inter operator agreement rate. This rate is a critical measure of the consistency and agreement level among test results. Such a metric is invaluable to healthcare professionals, as it enhances their understanding and trust in the model's consistency and reliability.

MARIE.AI

Marie.AI stands as a seminal advancement in the realm of healthcare technology. This multimodal artificial intelligence model epitomizes an exhaustive compendium of health-related information, integrating a broad spectrum of medical insights and resources. The platform's distinguishing feature is its expansive database, encompassing over 32 million health data points.

O modelo da Marie.AI foi desenvolvido ao longo de cinco anos com uma estrutura de ontologia médica para organização dos dados, para isso utilizamos o projeto OpenEHR. Ao longo desses anos, desenvolvemos os algoritmos de visão computacional e inteligência artificial.

No ano de 2020, em frente a pandemia da COVID-19, iniciamos parcerias com municípios em Unidade de Saúde no Estado de Minas Gerais - Brasil para apoiar no diagnóstico de COVID-19, Tuberculose e outras pneumonias. Os modelos de inteligência artificial seguiram os pressupostos da Teoria da Computação de Shannon,

The concept of Precision Medicine has been recently introduced as a progressive model for healthcare delivery, emphasizing a predictive, preventive, personalized, and participatory approach. Integral to Precision Medicine is its reliance on data-intensive methodologies, encompassing the realms of machine learning and artificial intelligence, which are pivotal for its development. To ensure the effective evolution of this paradigm, we adhere to four foundational principles in data architecture and processing (Figure 6):

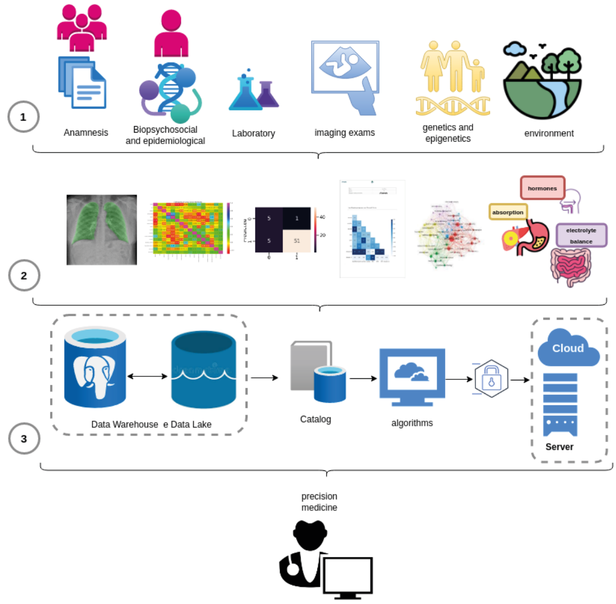

Figure 6. Attributes of the technological solution (particularities, characteristics)

Source: Author's compilation

(1) Have computer learning approaches powered by well-organized and sophisticated integrated data ecosystems. It is a multimodal model, with the input of scientific data, epidemiological data, clinical exams, imaging exams (X-ray and Computed Tomography);

(2) Due to the diversity of data, there is a system built on dynamic programming for pre-processing of the data and distribution to other deep learning models based on graph networks for processing image, textual, and biological data, which were modeled based on the minimum description length principle and stochastic models, and thus integrated to determine patterns of recognition, thus aiding in precision medicine. We still have an essential aspect: the platform has a self-learning model, which has evolved from an ontology model in the last three years. The technology is proprietary and developed by the company;

(3) At this stage, we have a data lake structure for organizing data based on

medical ontology and anonymizing sensitive data. There is still a security system. We integrate the results with an external API or integration into multiple platforms for decision-making in betrayal and/or diagnostic support cases;

(4) In this way, to promote better insights for the physician in decision making. We must introduce the effects of biopsychosocial and epidemiological aspects as intrinsic characteristics of individuals, as a way to optimize Artificial Intelligence/Machine Learning.

This project represents a collaborative public-private partnership in Brazil, aimed at bolstering initiatives within the Unified Health System (SUS). Despite SUS's status as a public service, certain systemic weaknesses have been identified. Collaborations of this nature are envisioned to enhance the quality of services provided by SUS. In line with this objective, the MARIE.AI^8 platform was employed for a proof of concept. The primary goal of this initiative is to ascertain the efficacy of a pre-trained model, originally developed for X-Ray and Computed Tomography images, in accurately classifying Body Scan images. The ultimate aim is to determine whether this approach can be effectively utilized as a tool for tuberculosis tracking within penitentiary complexes.

One of the logical bases of MARIE.AI for screening tuberculosis is the characteristics found in patients with tuberculosis as a premise for the development of the logic (Table 1).

Condition	Found in images
activity suggestions	• Thick walled cavities • Centrilobular nodules with segmental distribution • Confluent centrilobular nodules • Nodules • Consolidations • Thickening of bronchial walls • Bronchial thickening • Bronchiectasis
Suggestions of inactivity (sequel)	• Thin-walled cavities • Traction bronchiectasis • Stretch marks • Emphysema • Mosaic pattern • Nodules

Table 1. Pathological findings of TB on images

TEST WITH MARIE.IA PLATFORM

Based on the x-ray imaging findings, we performed the first tests with the MARIE.AI platform. To identify the presence or absence of TB characteristics, the platform allows the insertion of the patient's clinical assessment data and the Body Scan image (Figure 7).

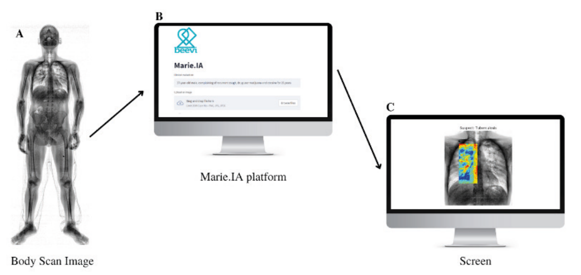

Figure 7. (A) Body Scan Image; (B) Artificial intelligence platform, where clinical evaluation data and image upload are entered; (C) Final result with identification of the altered area and the suspicion or not of TB.

CHARACTERISTICS OF IMAGES AND HARALICK EXTRACTOR

Studies show that chest radiographs are initially based on visualizing three characteristics[10]. They are (1) Anatomical structures, such as ribs and other bones, must be visible. (2) The darker (black in the image) the color of the lungs, the more suitable the functionality. (3) The heart and peripheral blood vessels must be visible. Using these characteristics, we applied the Haralick method[11] to extract texture characteristics through their attributes using a gray-level co-occurrence matrix. The co-occurrence matrix is a square matrix whose size is the number of gray levels in the image to be analyzed. The developer calculates the distances in all possible 360 degrees and normalizes between 0 and 100. Therefore, the co-occurrence matrix contains 100 rows per 100 columns and generates by combining the distances between the current angle and their respective combinations 10, 45, 90, and 135 degrees. After calculating this matrix, a matrix of the probability of the combinations between the gray levels was calculated. The following texture characteristics' values were calculated from this matrix: energy, entropy, variance, homogeneity, dissimilarity, and correlation measures.

HYPER PARAMETRIC SEARCH

In training a learning algorithm, hyperparameters are variables that in some way govern the model space or model-fitting procedure in order to reduce its generalization error thus. If, on the one hand, this peculiar characteristic of the hyperparameters makes it possible to obtain models with better prediction performance, on the other hand, a price is paid for the effort inherent in estimating optimal values. The estimation Optimal hyper parametric has challenges that are linked to the type of learning algorithm used, the cost function employed, and the training and test datasets, among others. Hyperparameter optimization is typically approached as a non-existent, single-objective, domain-restricted derivative problem[12]. A key issue in hyper parametric search is the cost of evaluating the objective function. Each evaluation requires calculating the performance of the trained model with a given(s) data value(s) for the hyperparameter(s). Depending on available computational resources. Due to the learning algorithm's nature and the datasets' size, each assessment can take minutes to several days[13].

The hyperparameter optimization of neural network models with deep architecture is a notable example of this situation, often requiring a large training dataset. Another point is that hyperparameters can have an evident influence on how much training time is, as in the case of neural network architecture[14]. Already for others, the influence can be subtle but of significant alteration in the performance of the model, given the regularization and kernel use cases[15]. Another critical factor in the hyperparameter search is the frequent existence of a stochastic component in the objective function[12], induced by factors linked to the model itself, such as initial values of the weights of a neural network, resampling of data used in training (as in the construction of a forest random), among others. This stochastic behavior implies that the set of optimal hyperparameters found empirically after some evaluations may not be valuable.

SELECTION OF PROBABILISTIC MODEL

The model selection problem refers to choosing the best model among a set of candidates built from combinations of parameters. Consider a sequence of models M1, M2, and Mn with the corresponding parameters. There are many techniques for selecting the best model based on the probability ratio, and others add different penalty functions to the likelihood ratio. This is the case of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), both of which test two models at a time, and the two can be chosen in ascending order of the number of parameters. After that, there is a sequence of BIC and AIC values, which are optimized. This results in the number of parameters to determine the best model. Therefore, in the present study, we used X-means[16], an algorithm that efficiently searches the space of the clusters' locations and the number of groups to optimize the measurement of the BIC. A decision tree was used to find the hyperparameter and inference tests to verify the training, testing, and validation of the model[17].

RESULTS

The stratified K-Fold approach used three scores: a minimum score of 0.95, a maximum score of 0.98, and an average score of 0.96. These results show that the average score of 0.96 presents a high assertiveness and indicates the model's high quality with actual data. Optimizing the decision tree's hyperparameters was to determine the model's best criteria, precision, and standard deviation (figure 8).

This resulted in three scores: a minimum score of 0.95, a maximum score of 0.98, and an average score of 0.96. These results show that the average score of 0.96 is highly accurate and indicates the model's high quality with actual data. Optimizing the decision tree's hyperparameters (figure 9) was to determine the model's best criteria, precision, and standard deviation.

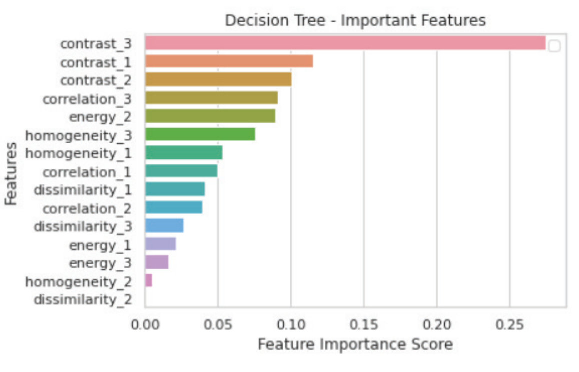

Figure 9. Most relevant characteristics for clustering the groups between suspected TB and non-suspected TB.

In this step, 510 Body Scan images were tested, and we obtained the following results, inserted in a confusion matrix (figure 10).

	Suspect TB	Not suspect TB
Suspect TB	416	0
Not suspect TB	12	82

Figure 10. Suspected TB X non-suspected TB: Sensitivity = 100% ; Specificity = 87,23%; Positive predictive value (PPV) = 97,2%; Negative predictive value (NPV)= 100%.

Lung segmentation was performed on the MARIE.AI. platform, which processed the images. For this test, the experimenter was unaware of the patient's signs and symptoms or any previous history of disease, so that we could observe the reproducibility of the results (Figure 11).

In this next set of images, we can observe that even the patients presenting some alteration, caused by another pathology, MARIE.AI did not identify alterations for tuberculosis (Figure 12).

DISCUSSION

The 2022 World Health Organization report recommends new methodologies for tuberculosis screening. Based on this fact, we performed a proof of concept to verify the feasibility of tuberculosis screening using Body Scan images in prisons. Using technologies already used generally for the entry and exit of prisoners and visitors is something present in the routine, not adding any aggravations or more significant risks to the health of passers-by in the prison complex. Also, we innovated in using a platform previously validated with radiography, computed tomography, and magnetic resonance[18].

Another relevant aspect is that the platform combines data from clinical exams with imaging exams and, thus, follows the tracking and underreporting standards described by

Best criterion	Best Maximum tree depth	Best number of components	Cross validation for model evaluation
Entropy	12	3	0,97 ± 0.05432

Figure 8. Hyperparameters values for the inference test.

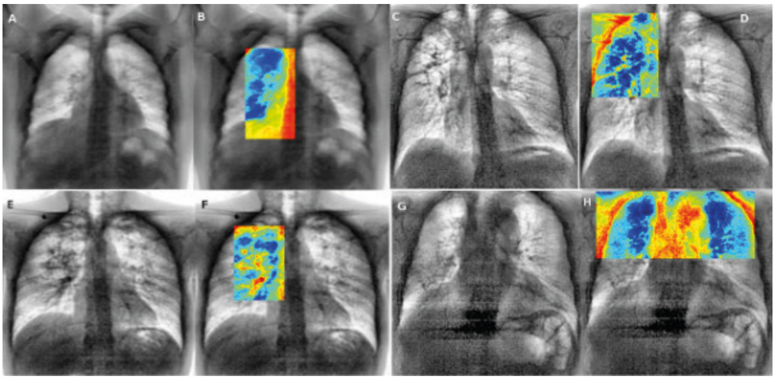

Figure 11. (A, C, E) Patient with suspected TB (B, D, F) Region with alteration detected by the anteroposterior image platform with alterations in the upper and middle lobes on the right side.;(G) Patient with suspected TB (H) Region with alteration detected by the anteroposterior image platform with alterations in both the right and left upper lobes.

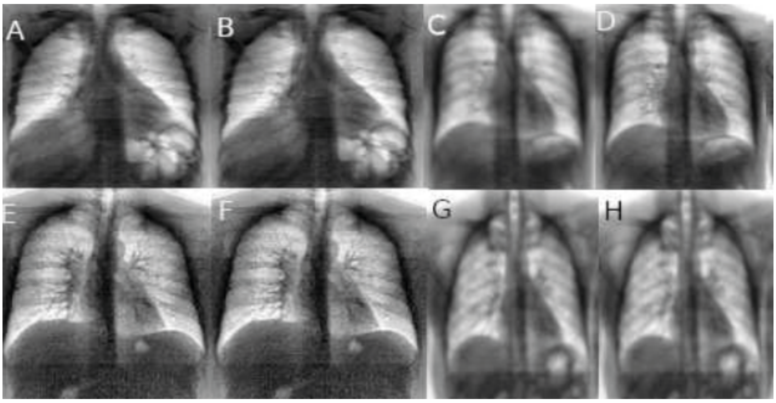

Figure 12. (A, C, E, G) Patient has no suspicion of tuberculosis or COVID-19; (B, D, F, H) For TB and COVID-19 the model did not detect any pattern.

the Ministry of Health and WHO, since the gold standard for the diagnosis of tuberculosis is based on evaluating X-ray results initially and later after seven days of smear. Given the extraordinary demand and the drop in notifications and underreporting, using methodologies based on artificial intelligence can help the health team to identify the incidence and prevalence of cases in this population, since there is an entry of visitors and prisoners on holidays determined by Brazilian law.

The advantages of implementing this system are that it can reduce the time of care and the beginning of treatment for people deprived of their liberty since the data collected in the medical records indicate a delay in the conclusion of tuberculosis by the radiographic examination, as there is a need for logistics and bureaucracy between public security and hospitals to move this patient for the exam[19]. As a result, there is lethargy in the system and, as a result, diagnosis can take an average of 2 to 3 months, thus intensifying the spread of tuberculosis among all transients who have access to the prison complex. Also, we highlight the improvement in service, operational efficiency, cost reduction, and increased productivity of the healthcare team in tracking, monitoring and reporting[20].

In this study, we used an artificial intelligence platform, MARIE.AI8, to evaluate the Body Scan images of patients with TB and patients who did not have Normal TB or any other pulmonary pathology. We used this method to verify whether pattern recognition for TB could be distinguished from any other group. We decided to use the platform with the model already trained and used in genuine cases in the municipality of Itapeva-MG, Brazil. Currently, the model has 1.000.000 lung images[18], 268.000 of which are x-raying images of patients with tuberculosis.

During the pandemic, we performed 18,000 validated cases of COVID-19, tuberculosis, lung cancer, and pneumonia. We are evaluated and confirmed by clinical and laboratory tests. In this way, we created two simple outputs for the proof of concept in the complex prison patients with suspected TB and patients not suspected of TB; in the analysis, we can see that the platform presented high performance as a screening proposal, with results of 100% for sensitivity and 87.23% for specificity. A screening test must have excellent sensitivity and specificity to result in low false-positive rates and to assure that the person does not have the disease when the result is negative. Sensitivity and specificity are inherent properties of each diagnostic test. These have a sensitivity (ability to detect individuals with that disease) and specificity (ability to exclude the diagnosis in cases of non-ill patients) that are never simultaneously 100%. In this way, our data show the quality of the experiments so that we can advance in the study of tuberculosis screening and possibly expand to the screening of other pulmonary pathologies. Another important aspect of this experiment was that the Body Scan images were delivered to the experimenter without prior knowledge of which of the groups he belonged to (TB or others).

On the other hand, we also overcame an obstacle, the difference in the construction of the images, since different wavelengths, and even so, produce them, the model could identify alterations that characterized aspects of tuberculosis. Still, we have that the Body Scan is a type of ionizing radiation; the chest X-ray emits about 1,000 times more radiation than the Body Scan[21], making it an almost insignificant amount about the other imaging exams, thus suggesting that in In the future, we can use less radiation in imaging exams when associated with multimodal artificial intelligence model software.

Another essential factor in reducing the error rate in the classification of imaging exams is that after the results, we analyze patients' histories to analyze each patient's clinical observations. In the group that suspected TB, we observed that the patient whose algorithm did not identify TB had a result between AFB (Ziehl-Neelsen) + or AFB (Ziehl-Neelsen) ++. In contrast, the other patients had AFB (Ziehl-Neelsen) +++, and the reports presented a persistent dry or productive cough. Furthermore, the composition of the Body Scan images allowed MARIE.AI to identify a sufficient amount of patterns in the image to reclassify the patient in the TB group correctly. Our approach shows promising data suggesting a new approach for monitoring and tracking TB in prison settings so that isolation measures, confirmation, and treatment of TB can enable the search for the reduction and eradication of TB in these settings.

Our experiment corroborates with several machine learning models using health data developed and published recently, achieving impressive results in tasks such as bone age assessment[22] and breast cancer detection[23].

However, these models were built based on a single modality or data type, thus helping decision-making.

However, these models rescued little from artificial intelligence, which is the ability of technological solutions to simulate human intelligence, performing certain activities autonomously and learning independently, receiving input from their users.

We have observed using different modalities and types of data to develop artificial intelligence solutions. This new revolution, using multimodal models[24], allows for finding different relationships between variables and characteristics visible or known by health professionals. We can also point out that these models can obtain a broad patient image since they can process millions of data in parallel, such as epidemiological data, risk factors, and tumor markers, extract image characteristics, and work with genomic profiles.

In our project, the gain of a multimodal model was apparent because even by inserting Body Scan images, the model was able to identify essential characteristics for the screening of tuberculosis; this new perspective opens a new area of study in which multimodal models can identify small patterns and in this way allow the doctor a continuous follow-up of the patient.

Multimodal models can be a new form of tracking and early diagnosis of pathologies.

World Health Organization guidelines show that tracking pathologies have more significant and beneficial effects at a lower cost than programs carried out on demand or health promotion, in addition to causing less damage. Calling and monitoring the population make it possible to reach the individuals who must undergo the examination at the recommended age and frequency, reducing the possibility of unnecessary repetition of examinations and screening in individuals outside the target population.

CONCLUSION

For this project, our results showed that MARIE.AI is a potential model for tracking Body Scan images in penitentiary complexes, as a support to the staff of this place to initiate sanitary and disease mitigation measures. However, a radiologist could easily understand and interpret the output of a machine learning model that segments consolidation lesions on a chest CT scan. It is easy to evaluate the result, and if the performance is impressive, you can establish confidence in the model.

However, the visualization of these alterations can be confusing for some physicians due to the difficulty of some professionals in identifying such alterations. Therefore, for the model to provide confidence to health professionals, we need to provide more transparency to the logic. For that, we must itemize the studies of possible parameters that may be more abstract due to the multiple inputs that are inserted in multimodal models.

In general, as a future perspective, our goal is to study aspects of the parameters and data that were used and how their weights determined the clustering of the groups and also identify the logical process as a bridge of greater transparency for physicians and thus allow greater security and confidence in the use of these models.

For this project, it was evident that a radiologist could easily understand and interpret the output of a machine learning model that segments consolidation lesions on a chest CT scan. It is easy to evaluate the result, and if the performance is impressive, it can establish confidence in the model. However, we came across new model parameters that reached more abstract expectations due to multiple inputs and the difficulty for some professionals to identify such features in a Body Scan image. In this context, as future objectives, we have the task of identifying means of interpreting the logic so that health professionals can have more clarity on the steps and parameters used and allow more security and confidence in using these models among physicians.

DATA AVAILABILITY

The datasets generated and/or analyzed during the current study are available in the article-images and MARIE.AI.IA-for-tuberculosis

https://drive.google.com/drive/folders/1U-xLElREDEuYbfcNqiGYy0_69g7YZ86wH?usp=sharing and https://github.com/paulinhac-nn/MARIE.AI.IA-for-tuberculosis.git

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REFERENCES

1. Jeremiah, C. et al. The who global tuberculosis 2021 report–not so good news and turning the tide back to end tb. Int. J.Infect. Dis. (2022).

2. Pai, M., Kasaeva, T. & Swaminathan, S. Covid-19's devastating effect on tuberculosis care—a path to recovery. New Engl.J. Medicine 386, 1490–1493 (2022).

3. Pai, M. Tuberculosis: the story after the primer. Nat. Rev. Dis. Primers 6, 1–2 (2020).

4. Marks, G. B. et al. A direct measure of tuberculosis incidence-effect of community screening. The New Engl. journal medicine 386, 1380–1382 (2022).

5. Reges Antonio Deon, S. d. S. F. J. M. d. A. E. A. K., Paula Cristina dos Santos. Tuberculose e covid-19: Aspectos clínicos, prevenção e controle no ambiente prisional. In COVID-19: Reflexões das ciências da saúde e impactos sociais 3, vol. 3, 67–78 (Atena Editora, 2021).

6. Fernandes, Máyra Rodrigues, et al. "Prevalência e fatores associados à presença de medicamentos vencidos em estoques caseiros." Cadernos Saúde Coletiva 28, 390-399 (2020).

7. de Almeida, T. T. S. et al. Tuberculose pulmonar no rio de janeiro: Um recorte temporal. Cadernos ESP 16, 19–26 (2022).

8. Santos, P. Intelligent computational model for the classification of covid-19 with chest radiography compared to other respiratory diseases. arXiv preprint arXiv:2108.05536 (2021).

9. da Silva, E. W. M. & Machado, C. J. Tuberculose: desafios e estratégias para o combate à doença no contexto brasileiro:(resenha do livro: Brasil. ministério da saúde. recomendações para o controle da tuberculose: guia rápido para profissionais de saúde. brasília, 2021). Revista Saúde. com 18 (2022).

10. Capone, R. B. et al. Tomographic aspects of advanced active pulmonary tuberculosis and evaluation of sequelae following treatment. Pulm. medicine 2017 (2017).

11. Löfstedt, T., Brynolfsson, P., Asklund, T., Nyholm, T. & Garpebring, A. Gray-level invariant haralick texture features. PloS one 14, e0212110 (2019).

12. Claesen, M. & De Moor, B. Hyperparameter search in machine learning. arXiv preprint arXiv:1502.02127 (2015).

13. Krizhevsky, A., Sutskever, I. & Hinton, G. E. Imagenet classification with deep convolutional neural networks. Commun. ACM 60, 84–90 (2017).

14. Bishop, C. M. & Nasrabadi, N. M. Pattern recognition and machine learning, vol. 4 (Springer, 2006).

15. Murphy, K. P. Machine learning: a probabilistic perspective (MIT press, 2012).

16. Pelleg, D., Moore, A. W. et al. X-means: Extending k-means with efficient estimation of the number of clusters. In Icml, vol. 1, 727–734 (2000).

17. Mantovani, R. G. et al. An empirical study on hyperparameter tuning of decision trees. arXiv preprint arXiv:1812.02207(2018).

18. Bento, V., Salaroli, B. F. & Santos, P. MARIE: Validation of the artificial intelligence model for covid-19 detection.

19. Silva, B. d., Temoteo, R., Véras, G. C. B. & Silva, C. Fatores predisponentes de tuberculose em indivíduos privados de liberdade: revisão integrativa. Arquivos de Ciências da Saúde 26, 67–71 (2019).

20. Tavares, M. L., Arara, M. A. & Lima, R. N. A assistência de enfermagem em homens privados de liberdade com tuberculose pulmonar. Revista Brasileira Interdiscip. de Saúde (2020).

21. Mettler Jr, F. A., Huda, W., Yoshizumi, T. T. & Mahesh, M. Effective doses in radiology and diagnostic nuclear medicine: a catalog. Radiology 248, 254–263 (2008).

22. Dallora AL, Anderberg P, Kvist O, Mendes E, Diaz Ruiz S, Sanmartin Berglund J. Bone age assessment with various machine learning techniques: A systematic literature review and meta-analysis. PLoS One. Jul 25;14(7):e0220242 (2019).

23. Geras KJ, Mann RM, Moy L. Artificial Intelligence for Mammography and Digital Breast Tomosynthesis: Current Concepts and Future Perspectives. Radiology.Nov;293(2):246–259 (2019).

24. ACOSTA, Julián N. et al. Multimodal biomedical AI. Nature Medicine, v. 28, n. 9, p. 1773-1784, 2022.

25. World Health Organization. Global action plan for the prevention and control of NCDs 2013–2020. Geneva: WHO, 2013. (WHO guide for effective programmes, module 3). Disponível em: https://www.who.int/news-room/fact-sheets/detail/cancer. Acesso em: 26 Apr. 2023.