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Machine learning-based model for estimating mortality risk in patients with traumatic brain injury, Ethel Kandler Hospital

Modelo basado en aprendizaje automático de estimación de riesgo de mortalidad en pacientes con trauma craneoencefálico, Hospital Ethel Kandler

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ABSTRACT

Artificial Intelligence and medicine have found various points where they converge, changing the concept of health. Among the problems of immediate attention is Traumatic Brain Injury (TBI), which constitutes an important public health problem in all countries; every day in the world, about 16,000 people die from trauma. This study aims to develop a Machine Learning-based model to estimate the probability of mortality risk in patients with TBI. The project was developed at the Ethel Kandler Hospital of the Corn Island municipality of the South Caribbean Coast Autonomous Region under the SCRUM methodology, which allowed continuous feedback on the proposed model. The Machine Learning algorithms selected for the construction of the model were the Random Forest and K-NN, the dataset for the initial model was the CRASH-2, and all analysis and processing were done in Python. The model has been shown to be able to predict with acceptable accuracy the probability of mortality in patients with TBI. However, Random Forest performed better; on average, it was 87.06% effective, while K-NN was 77.87%. The results were promising, and the study offers an encouraging prospect for the development of future Machine learning-based prediction models. Importantly, this model is complementary to clinical decision-making and should not replace clinical judgment.

Keywords: Brain, algorithms, prediction.

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RESUMEN

La Inteligencia Artificial y la medicina han encontrado varios puntos en los que convergen, cambiando el concepto de salud. Entre los problemas de atención inmediata se encuentran los traumas craneoencefálicos (TCE), que constituyen un importante problema de salud pública en todos los países, cada día en el mundo, alrededor de 16.000 personas mueren por traumatismos. Este estudio tiene como objetivo desarrollar un modelo basado en Aprendizaje Automático para estimar la probabilidad de riesgo de mortalidad en pacientes con TCE. El proyecto se desarrolló en el Hospital Ethel Kandler del municipio Corn Island del Región Autónoma Costa Caribe Sur, bajo la metodología SCRUM, la cual permitió la retroalimentación continua del modelo propuesto, los algoritmos de Aprendizaje Automático seleccionados para la construcción del modelo fueron el Random Forest y K-NN, el conjunto de datos para el modelo inicial fue el CRASH-2, todo el análisis y procesamiento se realizó en Python. Se ha demostrado que el modelo es capaz de predecir con una precisión aceptable la probabilidad de mortalidad en pacientes con TCE, sin embargo, Random Forest tuvo un mejor desempeño; en promedio tuvo una efectividad del 87,06%, mientras que la K-NN fue del 77,87%. Los resultados fueron prometedores, y el estudio ofrece una perspectiva alentadora para el desarrollo de futuros modelos de predicción basados en Aprendizaje Automático. Es importante destacar que este modelo es complementario a la toma de decisiones clínicas y no debe reemplazar el juicio clínico.

Palabras claves: Algoritmos, cerebro, predicción

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INTRODUCTION

Over the past decade, smart technologies and medicine have found various points where they converge. Advances are changing the concept of health, and health needs are influencing the development of the field (Avila-Tomás et al., 2020). Regardless of which countries lead the Artificial Intelligence (AI) initiatives, universities have begun to form multidisciplinary groups that offer new and innovative perspectives in this area of knowledge, among the lines of interest highlights AI applied to medicine, this line aims to seek medical solutions through the application of intelligent technologies. Among the most used technologies is Machine Learning (ML); Used in "radiological images, pathological anatomy preparations and electronic medical records of patients, in order to assist in the process of diagnosis and treatment of patients" (Ávila-Tomás et al., 2021). For this, the computer is provided with a large amount of data (Big Data) each of these with the label corresponding to the concept to be recognized in order to train a data set that is capable of predicting epidemics, improving therapeutic schemes, advising doctors in remote places and improving the quality of life of patients (Arias et al., 2019).

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Among the problems of immediate attention are Traumatic Brain Injuries (TBI), which constitute an important public health problem in all countries (Charry et al., 2019), this is defined as a structural injury and / or physiological alteration of brain function induced by trauma due to an external force, being one of the main causes of morbidity and mortality worldwide in patients under 45 years of age (Borja Santillán et al., 2021). It is clinically classified as mild, moderate, and severe by Glasgow Coma Scale (GSC) (Herrera Martínez et al., 2018). According to the World Health Organization (WHO), (n.d.), every day in the world, about 16,000 people die from injuries, representing 12% of the global burden of disease, the third most important cause of overall mortality and the leading cause of death in the age group of 1 to 45 years. Even so, in most countries' trauma is typically considered an accident, with little effort committed to research for the study and reduction of this disease (Montero, 2012). According to Giner Giner et al. (2002), it is one of the leading causes of death and disability worldwide. It causes the majority of trauma deaths, with a rate of 579 per 100,000 person per year, mainly due to falls or vehicular accidents. It greatly affects third world countries, which represents almost all of Latin America. The incidence of TBI varies considerably depending on the country or continent being studied; mortality from TBI is much higher in developing countries such as Nicaragua than in first world countries due to the delay of care in health services (Herrera Martínez et al., 2018).

The World Health Organization (WHO) (2018) predicts that by 2030 TBI will surpass other situations as a cause of death and disability. It represents an important global health problem, impacts health systems by the treatment of patients, new diagnostic tools, neurosurgery centers, and implies a series of consequences for the quality of life of the individual and a considerable expense for the States (Bravo Neira et al., 2019). The correct diagnosis of the state of patients with TBI has become a problem of great impact in the medical community due to the uncertainty of this process when using the GCS as the only tool to determine the status of a patient, the score is based on the skill of the observer, since, two people may rate a patient's assessment differently, especially if they are untrained. This suggests a problem in the South Caribbean Coast Autonomous Region (RACCS), especially in the municipality of Corn Island, given the little specialization in the area, so this problem must be addressed, with the aim of providing solutions that promote more objective and accurate results when carrying out the evaluation of patients with TBI. In order to strengthen the health system, a ML- based model is proposed to estimate the probability of mortality risk in patients with TBI of the Ehtel Kandler hospital, which allows estimating the probability of mortality risk in these patients from clinical parameters to provide better care.

State of the art

ML is a branch of AI used successfully in multiple areas. "In recent years with the increasing availability of electronically stored clinical information, the medical field has become an ideal environment for the development and application of this technology" (Álvarez Vega et al., 2020). In the beginnings of medicine, doctors worked in a closed ecosystem, doctors working together looking to solve problems, currently, that model is not functional; medicine has become more complex, many more therapies, drugs, examinations are available, and processing these data exceed the capacity of understanding of the human mind (Obermeyer & Lee, 2017). For this reason, the need to develop tools that are capable of assisting doctors in clinical processes.

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The use of ML in the medical field is wide, it can practically be applied in all medical specialties. The large amount of data accumulated over time provides the right context to develop models capable of making clinical predictions. Clinical prediction models aim to predict patient outcomes, to inform diagnosis or prognosis, hundreds of prediction models are published in the literature every year, but many are developed using a dataset that is too small for the total number of the study population, this leads to inaccurate predictions (Riley et al., 2020). On the other hand, the most common error employed in multiple outcome predictions is to derive a model for each outcome separately and then multiply the predicted risks. In case of multiple outcomes, four approaches are recommended: probabilistic classification chain, multinomial logistic regression, multivariate logistic regression, and the Bayesian probit model (Martin et al., 2021). ML algorithms involve different techniques, in particular neural networks, decision trees, and Bayesian networks, having a great development and impact on clinical prediction models (Montero Rodríguez et al., 2019).

It is anticipated that new AI technologies that integrate ML will substantially influence healthcare. Each day, ML is becoming more relevant in medicine, and ML focuses on making accurate predictions, while traditional statistical models aim to infer relationships between variables. "The benefits of ML comprise flexibility and scalability compared to conventional statistical approaches, making it useful for various tasks, such as diagnosis and classification, and survival predictions" (Rajula et al., 2020).

The ML algorithms applied in mortality prediction of TBI are several, Matsuo et al., (2020), made a comparison of nine algorithms: ridge regression, LASSO regression, random forest, gradient boosting, extra trees, decision tree, gaussian naive bayes, multi-nomial naive bayes and support vector machine. The ridge regression algorithm demonstrated the best performance for mortality prediction; with almost 90% accuracy. The most prominent variables in these models were age, GCS, fibrin/fibrinogen degradation products, and glucose. The most notorious limitation was the lack of external validation of the algorithm with the best result. Unlike the previous study, where they compared existing algorithms, Raj et al., (2019) focused their efforts on the creation of two algorithms capable of predicting mortality in real-time during intensive care after traumatic brain injury. They implemented ML-based logistic regression models taking into account Blood Pressure (BP), Cerebral Perfusion Pressure (CPP), and GCS to predict mortality at 30 days. They used a stratified cross-validation technique for internal validation. They had an accuracy of 81% and 84%, but like the study by Matsuo, this study lacks external validation.

"The incidence of TBI varies considerably depending on the country or continent being studied; TBI mortality is much higher in third world countries than in first world countries" (Herrera Martínez et al., 2018). It is important to understand the behavior of predictive variables in the population of low and moderate-income countries (LMIC). There are few attempts to generate prediction models for TBI outcomes from local data in LMIC, hence the relevance of the study conducted by Amorim et al., (2020), where they designed and compared a series of predictive models of mortality in TBI patients in Brazil using ML. The variables considered were sex, age, pupillary response, GCS, presence of hypoxia and hypotension, Computed tomography (CT), Respiratory Rate (RF), and Systolic Blood Pressure (SBP); the model had a success of 22.85% in

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14 days. The algorithm with the best result on this occasion was random forest; it should be noted that external validation was done.

There is limited information on in-hospital mortality prediction models for patients with TBI admitted to emergency departments. However (2021) developed a prediction model that, using clinical and demographic measures, estimates the mortality of patients with TBI admitted to the emergency department. The most significant variables were GCS, injury severity assessment (ISS), Heart Rate (HR), and Systolic Blood Pressure (SBP). In this study, the J48 algorithm demonstrated the best results, with an accuracy of 93.2%.

It is indisputable that the Python programming language excels in the construction of predictive models in TBI patients. The process of developing ML models usually has a quantitative approach involving numerical calculations and data analysis. In this context, it is normal to think of libraries such as Numpy, SciPy, Pandas, or Numba because they are the ideal Python libraries for data analysis and numerical computation. However, they are not the primary libraries applied to the construction of these models. Scikit-learn is the primary; it is a library specifically for ML development and data analysis, and it is designed to interact with NumPy, SciPy, and Matplotlib; its main advantages are its ease of use and the large number of ML techniques it implements.

MATERIALS AND METHODS

Studio Design & Environment

The project was developed at the Ethel Kandler Hospital of the Corn Island municipality of the RACCS, under the SCRUM development methodology, which allowed continuous feedback of the proposed model. We included all patients over 16 years of age with TBI seen in the emergency department between 2020-2021 and excluded patients who did not meet these criteria. An exhaustive review of the state of the art was carried out to assess different types of ML algorithms applied in the development of predictive models and to identify the determining variables in the prediction of mortality in patients with TBI. All analysis and processing were done in Python.

Definitions

The ML algorithms selected for the construction of the predictive model were the Random Forest and K-Nearest Neighbors (K-NN), the dataset for the initial model and the internal validation was the Clinical Randomization of an Antifibrinolytic in Significant Haemorrhage (CRASH-2). The selected variables were age, sex, ethnicity, Glasgow Coma Scale (GSC), Systolic Blood Pressure (SBP), Diastolic Blood Pressure (DBP), Heart Rate (HR), Respiratory Rate (RR), Significant Head Injury, and Oxygen Saturation (Table 1). It is worth mentioning that ethnographic variables are not determinant in the prediction, but they were included for future studies.

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Table 1

Predictive variable for mortality in patients with TBI

#	Variables	Input instrument	Unit	Monitoring frequency
1	Age		> 16	
2	Sex		Male/Female	
3	Ethnicity		Ethnic group	
4	GSC		3 - 15	
5	SBP	Clinical record	120 - 179	Ones
6	DBP		80 - 109	
7	HR		12 - 20	
8	RR		60 - 100	
9	Significant Head Injury		Yes/No	
10	Oxygen Saturation		%	

Classification and preparation of training data

It was conducted on the CRASH-2 dataset, which contains more than 20,000 randomized TBI patient records from 24 hospitals in 40 countries. The object column (death) was identified, which allowed the distinction between deaths and survivors, adjusting its value to 1-0, being one survivor and 0 death. The 10 variables defined previously were classified using feature selection algorithms to measure the importance of the predictive variables. Even so, there was no discrimination from the previous selection. Subsequently, all other variables in the dataset were amputated, such as null and duplicate values. The dataset was randomly divided, 80% for training and 20% for internal validation.

Training and internal validation

The output variable of the model was mortality in patients with TBI. Two supervised learning algorithms were trained for mortality prediction, the Random Forest and the K-NN; That, unlike unsupervised learning, in supervised learning the training data is labeled and the learning algorithm is trained to predict labels for unseen data.

The random forest (Figure 1 (a)) is a widely used algorithm that combines the result of multiple decision trees to achieve a single result. Its ease of use and flexibility have driven its adoption, as it handles both classification and regression problems (IBM, n.d.). K-NN (Figure 1 (b)), is one of the simplest classification algorithms, even with such simplicity it can give highly competitive results, it is a learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual dataset (Díaz, n.d.).

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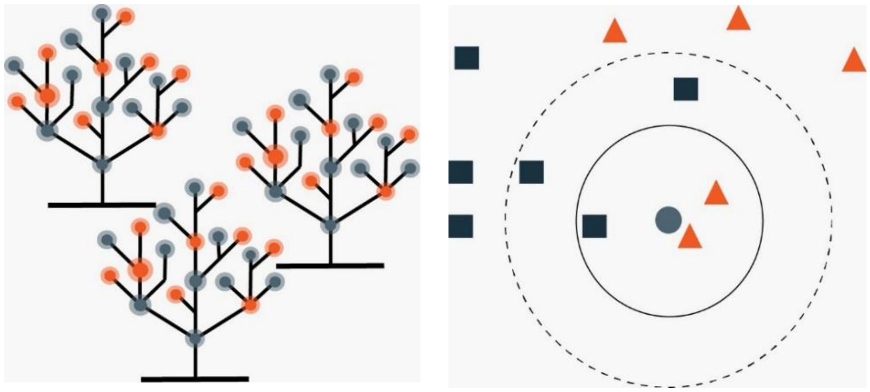
Figure 1

Algorithms trained for mortality prediction



(a) (b)

(a) Random Forest, (b) K-NN

The dataset was randomly divided with the function train_test_split, 80% for training and 20% for internal validation, standardization; was performed using klearn.preprocessing.StandardScaler. The goal of the standardization was to bring the features to a similar scale, which is expected to improve the performance of the models. This method transforms the data so that the mean of each characteristic is equal to 0 and the standard deviation is equal to 1; the SMOTE function was used to balance our data so that there are no more positive cases than negative cases. Each algorithm was trained separately to perform a comparison of its performances.

To train and internally validate the models, we use cross-validation. Each model was repeated with different samples of training and test sets for repeatability of results, this is a technique for evaluating ML models by training more than one learning algorithm. The metrics used to define the best-performing model were accuracy, sensitivity, specificity, and the ROC (Receiver Operating Characteristic) curve (Table 2).

Table 2

Metrics used to define the best-performing model

Metrics	Meaning
Accuracy	It indicates the model's ability to predict true positives and true negatives.
Sensitivity	It indicates the model's ability to detect true positives, i.e., the model's ability to correctly identify positive cases.
Specificity	Indicates the model's ability to detect true negatives, i.e., the model's ability to correctly identify negative cases.
ROC curve	Shows the relationship between the true positive rate (Sensitivity) and the false positive rate (Specificity) as the model's decision threshold is adjusted.

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Usability of the model

The usability of the model was carried out in two moments, first the resulting model was presented to the authorities of the municipality of Corn Island (Mayor of the municipality, Director of the Etherl Kandles Hospital, Political Secretary of the municipality, Director of BICU-Corn Island and Director of the research and postgraduate department of the BICU university), in order to receive feedback and guarantee through agreements access to the hospital's clinical registry to carry out the external validation of the final model in the next phase of the project. Subsequently, the model was presented to the clinical staff of the hospital (nurses, general practitioners and specialist doctors), in order to ensure interaction with the model to evaluate its usability and collect feedback to ensure an appropriate model to their context.

RESULTS AND DISCUSSION

Development context

The leading causes of TBI patients treated at the Ethel Kandler Hospital is traffic accidents, which account for 80% of the cases attended, mainly in motorcycle accidents. It is noteworthy that the municipality of Corn Island, as of October of 2023, stood out in the first place of traffic accidents in the RACCS, alarming numbers considering that it is one of the smallest municipalities in this region, if not the smallest. Even so, the ability to determine the status of TBI patients at Ethel Kandler Hospital is limited to the GSC; Not very adequate, considering that this evaluation is subject to the personal discretion of the doctor, and each doctor may give a different GSC score to the same patient. This provides the opportunity to incorporate the proposed model as a support tool in the care and follow-up of these patients.

Although the model does not suggest a follow-up strategy, it reflects clear indicators of patients that require follow-up due to the probability of mortality resulting from the predictive model, indicating a significant contribution to decision-making in the care of these patients.

TBI management

The only tool used at the Ethel Kandler Hospital to detect the state of patients with TBI is GSC, it does not have a management strategy for the follow-up of patients with TBI and there is no classification of these patients. Patient records are by year of birth, regardless of the admission reason.

ML model performance

The primary metric used to evaluate the performance of the different models trained was the ROC Curve, it shows the relationship between the true positive rate and the false positive rate of the model, is a commonly used metric to evaluate model performance. But, due to the nature of medical data, the metrics of accuracy, sensitivity and specificity was also included to define model performance.

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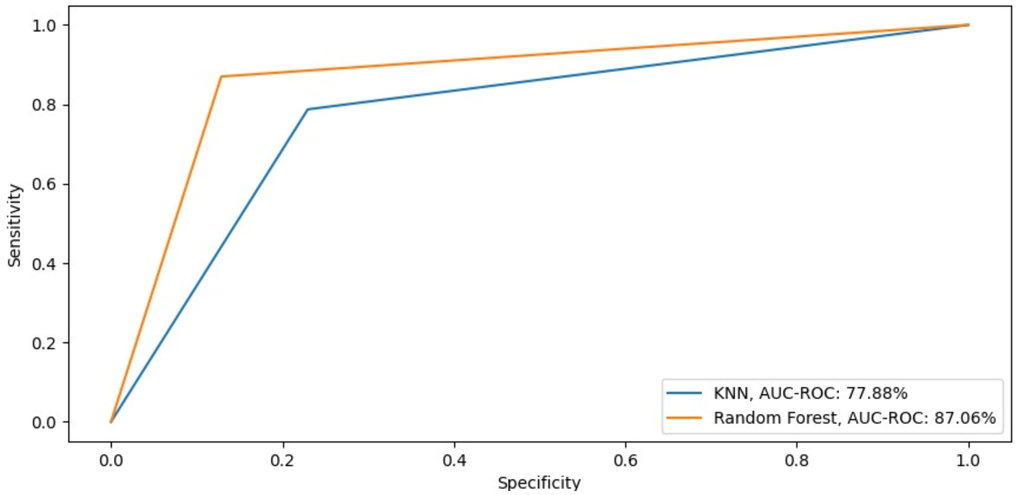
Figure 2
ROC Curve metrics



Source: (Sambola et al.)

The ROC Curve for the K-NN and Random Forest models were 77.88% and 87.06% respectively (Figure 2). An ideal ROC curve would be close to the northwest corner of the figure, which would mean that the model has a high rate of true positives, as can be seen in the Figure 2, Random Forest reflects better performance in detecting true positives. As for the other metrics, Random Forest obtained an accuracy of 87.06%, sensitivity of 86.72%, and specificity of 86.99%; on the other hand, K-NN obtained an accuracy of 77.87%, sensitivity of 76.81%, and a specificity of 78.72% (Table 3).

Table 3
Accuracy, Sensitivity and Specificity metrics

Metrics	Random Forest	K-NN
Accuracy	87.06%	77.87%
Sensitivity	86.72%	76.81%
Specificity	86.99%	78.72

In both models, the variables, GSC, SBP, DBP, HR, RR, Significant Head Injury, and Oxygen Saturation, demonstrated to have a significant impact on the prediction of mortality in patients with TBI. As for the variables age, sex, ethnicity showed less impact on the prediction.

Usability evaluation

After presenting the resulting model to the medical staff and achieving their interaction with it, a survey was applied to evaluate the usability of the model at the Ethel Kandler Hospital, in which a high rate of acceptability was identified. The results are shown in Figures 3-6, where the usefulness of the model, its interface, its ability to improve the care of patients with TBI, and its contribution to the technological development of the municipality were evaluated.

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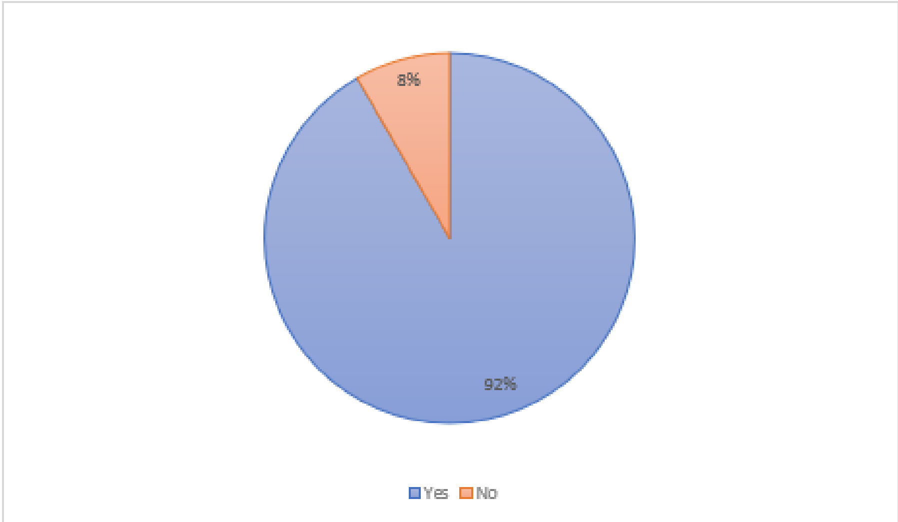
Figure 3

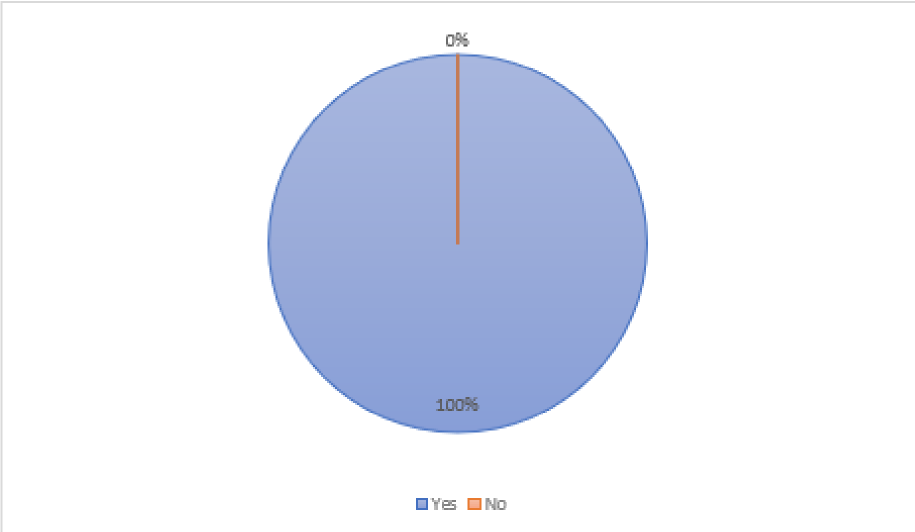
Usefulness of the model as a support for the care and follow-up of patients with TBI



Source: (survey applied by Sambola et al.)

Figure 4

The model would improve care for patients with TBI



Source: (survey applied by Sambola et al.)

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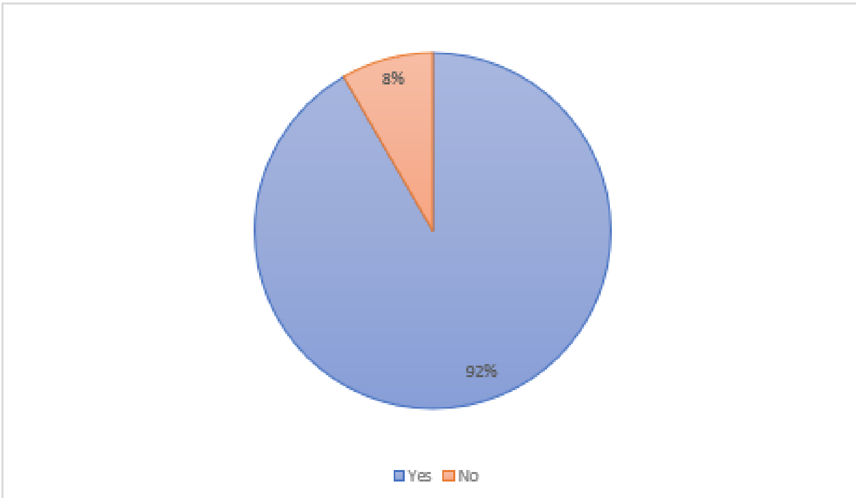
Figure 5

Contributes to the technological development of the municipality



Source: (survey applied by Sambola et al.)

Acceptance of Medical Personnel

It was possible to identify a high degree of acceptance towards the predictive model by the medical staff of the hospital; however, it is recommended to carry out a more in-depth study which involves specialists in the treatment of patients with TBI and the inclusion of the model in their day-to-day life to ensure that it is aligned with the specific needs and conditions of the hospital, thus achieving a greater understanding of the impact of the model and the effectiveness that it can have in the unique environment.

Model evaluation

The proposed model suggests an improvement in clinical care and decision-making at Ethel Kander Hospital. The implementation of ML in the medical field, specifically in the management of patients with TBI, has shown promise and can contribute significantly to the reduction of morbidity and mortality associated with this condition. The data cleansing process and the selection of the data source played a very important role in the final performance of the predictive model. The selection of predictive variables was appropriate; although ethnographic variables did not play an important role in the prediction, they are of great relevance in the multi-ethnic context of the population of this region, and they could not be excluded.

The model has been shown to be able to predict with acceptable accuracy the probability of mortality in patients with TBI, however, Random Forest performed better; on average it was 87.06% effective, while K-NN was 77.87%. However, it is important to consider some limitations and challenges, including the availability and quality of clinical data needed to feed the model and complete and accurate data for reliable predictions. In addition, further studies are needed to assess the efficacy and generalizability of the model in different contexts and population. External

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validation of the model and comparison with other mortality risk estimation prediction algorithms are also important aspects to consider. There for, as future step, it is intended to include other predictive algorithms to evaluate their mortality prediction performance in TBI patients, to include other hospitals in other municipalities in order to achieve a model suitable for RACCS, to carry out the external validation of the resulting model and to evaluate the usability of the model in a more appropriate context and time.

CONCLUSIONS

An ML-based model was developed to predict the probability of mortality in patients with TBI, generating medical solutions through the application of AI. The results were promising, presenting a high degree of acceptance by the health community. The study offers an encouraging prospect for the development of future ML-based prediction models. Importantly, this model is complementary to clinical decision-making and should not replace clinical judgment

Informed Consent Statement: Patient consent was waived due to data were collected through a non-participatory observation (clinical history) that did not involve direct contact with patients, on the other hand, the identity of the patients was not relevant to the study, therefore, they were kept anonymous.

CONFLICTS OF INTEREST

The authors declare no conflict of interest

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