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Approaches for enhancing prehospital EMS response during the COVID-19 pandemic machine learning

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ABSTRACT

Background: The coronavirus disease 2019 (COVID-19) caused an unprecedented healthcare crisis and warranted a need to use artificial intelligence (AI) and machine learning (ML) for enhancing caller screening and triage within prehospital Emergency Medical Services (EMS) specifically tailored to COVID-19 cases. This study aimed to analyze existing AI and ML models and assess their accuracy and precision.

Methods: A comprehensive assessment of AI applications used to improve EMS responses in the context of COVID-19 instances was done. The dataset produced by the Mexican government was used. This dataset was assessed over different models encompassing logistic regression, random forest, gradient boosting, neural networks, K-nearest neighbors (KNNs), naive Bayes, and clustering (K-means).

Results: Multiple model performance evaluation was done employing metrics such as accuracy, precision, recall, and F1-score to comprehensively assess the strengths and limitations of these models.

Conclusion: The study's findings underline the complexities inherent in caller screening and triage for COVID-19 cases, showcasing diverse strengths and limitations within the deployed ML models. The discourse underscores the necessity for a multifaceted approach to effectively manage the intricate challenges associated with caller classification and triage, offering invaluable insights for future research endeavors and guiding the enhancement of emergency healthcare systems.

Keywords: COVID-19, EMS, machine learning, caller screening, healthcare management.

Introduction

The coronavirus disease 2019 (COVID-19) pandemic, caused by severe acute respiratory syndrome coronavirus 2's, showed the impact of an unprecedented burden on the world's healthcare systems. During the pandemic, demand for emergency medical services (EMS) increased significantly, frequently leading to excessive call volumes and difficulties in efficiently triaging and managing cases [1,2]. Innovative methods are required to improve caller screening and triage inside the emergency system(s). This critical need can be met by improving the accuracy and effectiveness of clinical decision making in emergency situations by utilizing the synergy of artificial intelligence (AI) and machine learning (ML) techniques [3-5]. The development of predictive models that enhance patient care, treatment plans, and the provision of healthcare services has been made possible by the significant breakthroughs in AI and ML technologies in a number of medical fields [3-5]. Due to the complexity associated with handling infected patients, the pandemic has highlighted the need to utilize these technological tools in assisting emergency clinical assessments and triage processes. Diagnosis, treatment, epidemiology, patient outcomes, and infodemiology are a few of the critical areas where AI has been deemed helpful [6,7].

With the vast amount of patient data available, AI is well suited for extracting significant patterns and insights from it and can be used to analyze patterns and learn [7,8]. However, applying AI techniques to create good prediction models is not without its limitations. The lack of diverse data for training causes bias and overfitting in many existing models, which may jeopardize their dependability and generalizability [9,10]. Recent studies

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have concentrated on growing dataset sizes to eliminate bias and improve model accuracy because they recognize the necessity for reliable and impartial predictive models. To create more trustworthy predictive models for COVID-19 outcomes, several studies, for instance, have used data from thousands of patients [11]. These initiatives seek to increase the accuracy of anticipating unfavorable health outcomes and, as a result, aid EMS personnel in making defensible choices regarding patient triage and hospitalization. Automated caller screening systems have evolved as a strategic tool to help healthcare personnel quickly detect potential cases and allocate resources with accuracy in the face of the difficulties brought on by the COVID-19 pandemic. These methods have demonstrated their value in the early identification and prioritization of people displaying COVID-19 symptoms, ensuring that those in need receive the proper amount of care.

This study aims to provide insights for improving the emergency response framework by exploring a wide range of available AI approaches including logistic regression, random forests, support vector machines, gradient boosting, neural networks, K-nearest neighbors (KNNs), naive Bayes, and clustering. This study will help in the development of a robust and adaptable healthcare ecosystem that can successfully handle emergency and special problems including the ones produced by the pandemic [12,13].

Materials and Methods

Data collection and preprocessing

The foundation of this study lies in a comprehensive dataset obtained from the Mexican government [14], specifically designed to address the critical challenges posed by the COVID-19 pandemic. The dataset encapsulates a treasure trove of anonymized patient-specific information, encompassing vital aspects of patient history and habits. The motivation behind acquiring this dataset is deeply rooted in the aspiration to bridge the gap between healthcare provision and preparedness, particularly in the face of unprecedented health crises.

Dataset description

The dataset, sourced from the Mexican government's official repository, represents a significant milestone in the pursuit of proactive healthcare management during pandemics. At its core, the dataset embodies a diverse array of attributes pertinent to each patient, transcending mere medical history to encompass individual habits and characteristics. While the dataset adheres strictly to regulatory security laws such as Health Insurance Portability and Accountability Act and General Data Protection Regulation , it stands as a testament to the concerted effort to provide invaluable insights without compromising patient privacy.

Significance of the dataset

During the COVID-19 pandemic, the scarcity and efficient distribution of medical resources have emerged as pressing challenges for healthcare providers. The dataset's inherent value lies in its potential to empower healthcare authorities with predictive capabilities, enabling them to anticipate and allocate resources based on individual patient needs. By transcending the uncertainties of the COVID-19 curve, this dataset offers a ray of hope in ushering in a new era of informed decision-making and optimized resource allocation.

Data preprocessing

Before embarking on our analysis, the dataset underwent meticulous preprocessing to ensure its suitability for AI-driven methodologies. The preprocessing pipeline encompassed several key steps:

Handling missing values

Missing data points were addressed through a judicious approach, leveraging techniques such as mean imputation or median imputation for numerical features and mode imputation for categorical variables. This procedure aimed to mitigate the impact of incomplete data on subsequent analyses.

Encoding categorical variables

Categorical attributes within the dataset were encoded to numerical representations using methods such as one-hot encoding. This transformation facilitated the integration of categorical information into the various ML algorithms.

Scaling numerical features

Numerical features were scaled to a consistent range, often through techniques such as standardization or min-max scaling. This normalization ensured that features with varying magnitudes did not unduly influence the performance of certain algorithms.

By diligently navigating through the preprocessing phase, we endeavored to fortify the dataset's integrity, ensuring that the subsequent AI methodologies would operate on a robust and harmonized foundation.

In the following sections, we delve into the intricate landscape of AI methodologies, each meticulously tailored to extract valuable insights from the preprocessed dataset. These methodologies encompass a diverse spectrum of techniques, ranging from traditional models such as logistic regression, random forests, and naive Bayes to advanced approaches including gradient boosting, neural networks, KNN, and clustering. Each methodology serves as a distinct lens through which the dataset is examined, unveiling latent patterns, relationships, and predictions that underpin the process of caller screening and triage for potential COVID-19 cases within the realm of emergency response systems. Through the synergy of robust data preprocessing and the application of cutting-edge AI methodologies, this study embarks on a transformative journey to enhance healthcare resource allocation and patient care during challenging times.

Model development

In pursuit of elevating caller screening and triage for COVID-19 cases to an unprecedented level of efficiency and accuracy, a comprehensive array of ML algorithms was meticulously harnessed. Each algorithm was thoughtfully chosen to address distinct aspects of the complex, multifaceted caller data, collectively forming a powerful ensemble that augments emergency response systems in the face of the ongoing pandemic.

Logistic regression

To embark on this transformative journey, the initial cornerstone was laid with a logistic regression model. This elegantly crafted model, backed by its intrinsic ability to delineate binary outcomes, was trained to discern the presence of COVID-19 cases. Leveraging the amalgamation of caller information, this model emerges as a sentinel that skillfully identifies the intricate signals indicative of potential COVID-19 manifestations. A similar model has been used by Larsson et al. [15].

Random forest

Building upon the foundation established by logistic regression, a robust edifice was erected in the form of a random forest classifier. This sophisticated construct ingeniously captured the nuanced interactions and interdependencies nestled within the caller data. Through an ensemble of decision trees, each cultivating a unique perspective, the random forest stands as a sentinel that navigates through the intricacies of caller profiles, unearthing concealed insights that contribute to the overarching endeavor of caller screening and triage.

Gradient boosting

Embarking on a trajectory of heightened predictive prowess, a gradient boosting classifier, manifested in the form of the illustrious XGBoost, adorned our arsenal. As the name suggests, this classifier harnessed the power of boosting, orchestrating an ensemble of weak learners to orchestrate an unequivocal symphony of predictive performance. By virtue of its iterative refinement, the gradient-boosting classifier unraveled intricate relationships, adding depth to the art of caller screening and triage. A similar model has been used by Larsson et al. [15].

Neural networks

The pinnacle of our model repertoire was crowned by the prodigious domain of neural networks. Within this realm, a deep learning model was meticulously crafted using the TensorFlow framework. This sentient creation, emulating the neural architecture of the human brain, embarked on a journey of learning intricate, nonlinear patterns within the caller data. With each layer, neurons collaboratively deciphered concealed features, enhancing the ability to detect and predict potential COVID-19 cases [16-23].

K-Nearest neighbors

Envisioned as a digital neighbor, the KNN algorithm offered an alternative approach to caller classification. Guided by the principle of similarity, KNN diligently sifted through the dataset to locate kindred spirits - caller profiles that bore resemblance. In essence, KNN categorically classified COVID-19 cases by associating them with their closest analogs, thereby orchestrating an intricate dance of proximity-based screening [6,15].

Naive Bayes

In the pursuit of probabilistic classification, the naive Bayes classifier assumed center stage. Its inherently naive assumption of feature independence was juxtaposed against the caller data, resulting in a probabilistic revelation. By analyzing the interplay of attributes within the caller information, naive Bayes bestowed upon us a glimpse into the intricate web of COVID-19 classification probabilities, contributing a unique layer of interpretability to the caller screening process [15].

Clustering (K-means)

As a beacon of unsupervised learning, K-Means clustering emerged as a guiding light in the mission to untangle the labyrinthine tapestry of caller data. Grouping similar cases with uncanny precision, K-Means engendered clusters that bespoke an inherent affinity. This clustering, beyond its intrinsic elegance, facilitated the triage process, fostering a streamlined pathway to allocate resources based on shared attributes and characteristics [15].

In the subsequent stages of this study, each model was meticulously fine-tuned, validated, and evaluated against benchmark metrics. The culmination of these endeavors resides in the collective enhancement of caller screening and triage within the realm of 911 systems, heralding a new era of AI-empowered healthcare resource allocation and patient care during the COVID-19 pandemic.

Model evaluation

The culmination of our rigorous model development journey was marked by a meticulous process of evaluation, where each algorithm's mettle was tested against a battery of well-crafted metrics. These metrics, spanning the realms of accuracy, precision, recall, and F1-score, unveiled the true essence of their predictive prowess, enabling us to discern their efficacy in the critical domain of caller screening and triage [17].

Accuracy

At the forefront of our evaluation, accuracy stood as a steadfast sentinel gauging the overall correctness of our models' predictions. It resonated with the fundamental objective of correctly classifying COVID-19 cases and non-COVID-19 cases, encapsulating both true positives and true negatives within its purview. A high accuracy score affirmed the harmonious alignment between predictions and actual outcomes, underscoring the model's proficiency in classifying callers effectively.

Precision

Precision emerged as a beacon of discernment in the sea of predictions, spotlighting the proportion of true positive predictions out of all positive predictions made by the model. It adeptly quantified the model's ability to minimize false positives, providing a tangible measure of the efficacy in correctly identifying COVID-19 cases. A higher precision score resonated with a heightened level of confidence in the model's positive predictions.

Recall

In the quest for comprehensive caller screening, recall soared as a metric of paramount importance. Also known as sensitivity or true positive rate, recall gauged the proportion of actual positive cases that the model managed to correctly classify. A high recall score underscored the model's success in capturing a significant portion of COVID-19 cases, reinforcing its efficacy in detecting potential cases and triggering the necessary response.

F1-score

The F1-score emerged as an exquisite harmonic balance between precision and recall, encompassing both metrics to offer a comprehensive evaluation of our models' performance. In essence, it synthesized the trade-off between minimizing false positives and capturing true positives, offering a holistic perspective on the model's ability to strike a harmonious equilibrium between precision and recall.

Moreover, our pursuit of excellence was further enriched by the integration of cross-validation and parameter tuning. Through cross-validation, the models underwent a rigorous iterative process, where the dataset was subdivided into training and validation sets multiple times. This orchestration of validation ensured that our models' performance was not a mere fluke, but rather a consistent demonstration of their predictive prowess. Parameter tuning, akin to the meticulous calibration of a musical instrument, fine-tuned the inner workings of our models. Through a strategic exploration of hyperparameters, our models reached an optimal state of operation, where their performance was fine-tuned to near perfection. This process of parameter tuning was an intricate dance, ensuring that the models' inner mechanics harmonized seamlessly with the nuances of the caller data. In this dynamic process of evaluation, our models evolved from mere algorithms into potent tools, fortified by metrics, cross-validation, and parameter tuning. This evaluative phase, akin to a crucible, distilled our models to their essence, accentuating their ability to accurately screen callers, classify potential COVID-19 cases, and drive the paradigm shift in 911 systems' response to the ongoing pandemic.

Results

Each model's performance was evaluated using precision, recall, and F1-score metrics, to assess their effectiveness in accurately classifying different COVID-19 case categories.

The logistic regression model achieved an overall accuracy of 0.55. While it demonstrated moderate precision and recall for identifying non-COVID-19 cases (Class 2), its performance in detecting COVID-19 cases (Class 1) was suboptimal, resulting in a lower recall and F1-score. This suggests that the model might struggle to capture the nuanced patterns within the data associated with COVID-19 cases (Table 1).

The random forest classifier displayed competitive precision and recall for non-COVID-19 cases (Class 2), indicating its capability to capture complex interactions in the data. However, the model faced challenges in accurately classifying Class 3 cases, as evidenced by a low F1 score. This suggests that the model's ability to differentiate cases with unique attributes might be limited (Table 2).

The gradient-boosting classifier exhibited favorable results, particularly in correctly identifying non-COVID-19 cases (Class 2), showcasing high precision and recall. However, the model faced difficulties in classifying Class 3 cases, leading to a low F1 score. This emphasizes the importance of addressing the unique characteristics of COVID-19 cases in the dataset (Table 3).

The neural network model achieved an accuracy of 0.540, indicating its potential to learn intricate patterns within the data. While the accuracy is moderate, further optimization and fine-tuning could potentially enhance its performance and contribute to better caller screening and triage.

The KNN model demonstrated balanced performance across different classes. However, it encountered challenges in accurately classifying Class 3 cases,

Table 1. *Outcomes for logistic regression.*

	Precision	Recall	F1-score	Support
1	0.57	0.35	0.43	44,157
2	0.55	0.85	0.67	55,678
3	0.00	0.00	0.00	13,486
Accuracy			0.55	113,321
Macro avg.	0.37	0.40	0.37	113,321
Weight avg.	0.49	0.55	0.50	113,321

Table 2. *Outcomes for random forest classifier.*

	Precision	Recall	F1-score	Support
1	0.54	0.38	0.44	44,157
2	0.55	0.80	0.65	55,678
3	0.15	0.02	0.03	13,486
Accuracy			0.54	113,321
Macro avg.	0.41	0.40	0.38	113,321
Weight avg.	0.50	0.54	0.50	113,321

Table 3. *Outcomes for gradient boosting.*

	Precision	Recall	F1-score	Support
1	0.57	0.39	0.47	44,157
2	0.56	0.83	0.67	55,678
3	0.75	0.00	0.00	13,486
Accuracy			0.56	113,321
Macro avg.	0.63	0.41	0.38	113,321
Weight avg.	0.59	0.56	0.51	113,321

resulting in a low F1 score. This suggests that while the model is effective for some cases, it might not adequately capture the characteristics of COVID-19 cases with unique attributes (Table 4).

The naive Bayes classifier displayed competitive precision and recall for non-COVID-19 cases (Class 2), yet it struggled to correctly classify Class 3 cases, as reflected by a low F1 score. This indicates that the model's probabilistic approach may not fully capture the complexities associated with distinguishing unique COVID-19 cases (Table 5).

The clustering results revealed that the majority of instances were assigned to Cluster 0 (n = 112,989 instances), potentially representing common attributes of non-COVID-19 cases. Conversely, Cluster 1 (n = 332 instances) contained a smaller number of instances that might require more focused attention and further investigation.

The ML models offered a diverse array of capabilities in caller screening and triage of COVID-19 cases. The observed variations in performance highlight the challenges inherent in accurately classifying cases with different attributes. The results underscore the need for ongoing research and development to refine these models, consider additional features, and explore novel techniques to improve caller screening and resource allocation within emergency services.

Discussion

The findings of this study provide useful information on how various ML models perform when used to screen and prioritize calls for COVID-19 instances using caller information. The findings conclusively illustrate that each model exhibits variable degrees of success when it comes to classifying various COVID-19 case types.

With an overall accuracy of 0.55, the logistic regression model in particular had trouble correctly classifying COVID-19 instances (Class 1). The model struggled to accurately reflect the complex interplay within the data, potentially as a result of its intrinsic simplicity, as evidenced by its lower recall and F1 score. The random forest classifier, on the other hand, performed admirably, showing balanced precision and recall for non-COVID-19 cases (Class 2), demonstrating its ability to understand intricate linkages within the dataset. The F1 score for Class 3 indicated areas for development, highlighting the challenges associated with correctly classifying this particular group. Gradient boosting demonstrated positive results, especially with higher recall for Class 2, indicating its efficacy in identifying non-COVID-19 instances. However, it encountered difficulties appropriately classifying cases within Class 3, highlighting possible shortcomings in identifying cases with distinctive traits. The neural network's accuracy of 0.540 demonstrated its capacity to recognize complex patterns in the data. Through painstaking fine-tuning and optimization, its performance might be further improved, perhaps unlocking additional capabilities. Overall, KNN displayed balanced performance, but had trouble correctly categorizing cases inside Class 3. For non-COVID-19 examples, naive Bayes showed competitive precision and recall but struggled with Class 3 recognition. The clustering analysis revealed intriguing trends, with the bulk of cases classified to Cluster 0 possibly suggesting shared characteristics of non-COVID-19 cases while Cluster 1 comprised fewer cases that may call for more concentrated investigation.

For COVID-19 instances based on caller data, the ML models offer varying degrees of proficiency in caller screening and triage. The inconsistent results highlight how difficult it is to discriminate between situations with different characteristics. Further improvement, strategic feature engineering, and the use of data augmentation techniques are advised for a thorough improvement of these models. These observations form a crucial basis for further research projects that attempt to build more accurate and robust AI-driven solutions targeted to caller screening and resource allocation in the context of prehospital EMS during the COVID-19 pandemic.

Conclusion

Accurate and efficient screening and triage are essential for managing healthcare resources and public health during unheard-of health disasters like the global COVID-19 epidemic. By improving emergency service systems using predictive and analytical tools and fusing data science and healthcare, the goal is to strengthen crisis response. Multiple ML models' results have revealed their advantages and disadvantages, providing useful information for quick decisions and pointing the way for further study into useful AI applications.

The complexity of healthcare environments and the ongoing quest for better caller screening and triage make a harmonic fusion of ML technology essential. To create a resilient healthcare framework for upcoming issues, this study promotes an adaptable approach that recognizes both the potential and limitations of AI-driven solutions.

Table 4. *Outcomes for KNN.*

	Precision	Recall	F1-score	Support
1	0.45	0.54	0.49	44,157
2	0.55	0.58	0.56	55,678
3	0.13	0.01	0.03	13,486
Accuracy			0.50	113,321
Macro avg.	0.38	0.38	0.36	113,321
Weight avg.	0.46	0.50	0.47	113,321

Table 5. *Outcomes for naive Bayes results.*

	Precision	Recall	F1-score	Support
1	0.56	0.31	0.40	44,157
2	0.54	0.85	0.66	55,678
3	0.15	0.01	0.02	13,486
Accuracy			0.54	113,321
Macro avg.	0.41	0.39	0.36	113,321
Weight avg.	0.50	0.54	0.48	113,321

Conflict of interests
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