World Journal of Biology Pharmacy and Health Sciences
eISSN: 2582-5542
Cross Ref DOI: 10.30574/wjbphs
Journal homepage: https://wjbphs.com/

(Review Article)

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AI-driven risk stratification for targeted public health interventions

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World Journal of Biology Pharmacy and Health Sciences, 2024, 20(02), 988-994

Publication history: Received on 04 October 2024; revised on 13 November 2024; accepted on 16 November 2024

Article DOI: https://doi.org/10.30574/wjbphs.2024.20.2.0901

Abstract

The increasing complexity of public health challenges, particularly during infectious disease outbreaks, necessitates innovative approaches to identify and protect vulnerable populations. This study explores the use of supervised machine learning algorithms to stratify populations based on risk factors and predict severe outcomes during outbreaks. By leveraging demographic, clinical, and socioeconomic data, the proposed AI-driven models aim to enable healthcare systems to prioritize vulnerable groups, allocate resources effectively, and implement preventive measures. The results demonstrate the potential of AI in reducing mortality, improving health equity, and enhancing the overall resilience of public health systems. This research contributes to the growing body of knowledge on data-driven decision-making in public health.

Keywords: Artificial Intelligence; Risk Stratification; Supervised Machine Learning; Public Health Interventions; Health Equity; Resource Allocation; Outbreak Management

1. Introduction

Public health systems worldwide face significant challenges in managing infectious disease outbreaks, particularly in identifying and protecting vulnerable populations. The COVID-19 pandemic highlighted the critical need for targeted interventions to reduce mortality and improve health equity. Traditional approaches to risk stratification often rely on simplistic criteria, such as age or pre-existing conditions, which may not capture the full complexity of risk factors influencing severe outcomes [4]. Artificial intelligence (AI), particularly supervised machine learning (ML), offers a promising solution by enabling the analysis of complex datasets to identify high-risk individuals and predict severe outcomes. The primary objective of this research is to develop AI-driven models for risk stratification during infectious disease outbreaks. By leveraging diverse data sources, including demographic, clinical, and socioeconomic data, the models aim to provide actionable insights for healthcare systems [5].

These insights can guide the prioritization of vulnerable groups, optimize resource allocation, and implement preventive measures, ultimately reducing mortality and improving health equity. This study also seeks to address the limitations of existing risk stratification methods, such as their reliance on single risk factors and their inability to handle complex, multi-dimensional data. The integration of AI into public health decision-making represents a paradigm shift in how we approach outbreak management. Traditional methods often rely on static risk criteria and historical data, which may not capture the dynamic nature of disease transmission and individual risk profiles [7, 8]. In contrast, AI models can analyze real-time data, identify non-linear relationships, and adapt to changing conditions, enabling more accurate and timely risk stratification.

This study explores the potential of supervised ML algorithms, such as logistic regression, decision trees, and neural networks, in addressing these challenges. This research is particularly timely given the increasing availability of data

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from various sources, including electronic health records, wearable devices, and social determinants of health. By harnessing these data sources, AI models can provide a more comprehensive understanding of individual and population-level risk factors, enabling targeted interventions that improve health outcomes. The findings of this study have the potential to transform public health practice, enabling policymakers and healthcare providers to make data-driven decisions that reduce the impact of infectious disease outbreaks.

2. Literature Review

The application of AI in public health has gained significant attention in recent years, with numerous studies demonstrating its potential to improve risk stratification and outbreak management. For example, [1] developed an AI model to predict COVID-19 severity using clinical and demographic data. Their model achieved high accuracy in identifying high-risk patients, highlighting the potential of AI to enhance traditional risk assessment methods. Similarly, [2] conducted a systematic review of ML models for predicting COVID-19 outcomes, demonstrating the utility of these models in guiding clinical decision-making. Despite these advancements, most existing AI models focus on single diseases or specific populations, limiting their applicability in diverse public health contexts. Infectious disease outbreaks often affect populations with varying risk profiles, making it essential to develop models that can stratify risk across different demographic and socioeconomic groups [3]. This study addresses this gap by developing AI-driven models capable of stratifying risk across diverse populations and predicting severe outcomes during outbreaks.

Supervised ML algorithms, which learn from labeled data to make predictions, have shown promise in various healthcare applications. For example, [6] used supervised ML to predict hospital readmissions, demonstrating the potential of these algorithms to improve patient outcomes. In the context of risk stratification, supervised ML models can analyze complex datasets to identify patterns and predict severe outcomes, enabling targeted interventions [9, 10]. This study builds on previous research by exploring the use of supervised ML algorithms for risk stratification during infectious disease outbreaks The integration of diverse data sources is another critical factor in the success of AI models for risk stratification. Traditional models often rely on clinical data, such as laboratory results and medical history, which may not capture the full range of risk factors influencing severe outcomes. By incorporating demographic and socioeconomic data, AI models can provide a more comprehensive understanding of individual and population-level risk factors. For example, [11] used a combination of clinical and socioeconomic data to predict COVID-19 mortality, achieving high accuracy in their predictions. The use of real-time data is another area where AI models have a significant advantage over traditional methods. Real-time data, such as wearable device data and social media posts, can provide early warning signs of disease progression, enabling timely interventions. For instance, researchers have used wearable device data to predict influenza-like illness [12] and social media data to monitor mental health during the COVID-19 pandemic [13] These studies highlight the potential of real-time data to enhance the accuracy and timeliness of risk stratification.

Despite these advancements, several challenges remain in the application of AI models to public health. One major challenge is the availability of high-quality data, particularly in low-resource settings [14, 15]. Incomplete or inaccurate data can significantly impact the performance of AI models, leading to unreliable predictions. Another challenge is the interpretability of AI models, particularly in the context of public health decision-making. Policymakers and healthcare providers often require transparent and interpretable models to make informed decisions, which can be challenging with complex AI algorithms [17, 18].

This study builds on previous research by addressing these challenges and developing AI-driven models for risk stratification during infectious disease outbreaks. By leveraging supervised ML algorithms and diverse data sources, the proposed models aim to provide accurate and actionable insights for healthcare systems. The findings of this study have the potential to transform public health practice, enabling more effective and equitable responses to infectious disease outbreaks.

3. Body

3.1. Data Collection and Preprocessing

The success of AI models depends heavily on the quality and diversity of the data used for training. This study utilizes datasets from multiple sources, including demographic data (e.g., age, gender, ethnicity), clinical data (e.g., medical history, laboratory results), and socioeconomic data (e.g., income, education, housing conditions) [16]. Data preprocessing steps include handling missing values, normalizing features, and encoding categorical variables. The integration of diverse data sources ensures that the models capture the complex interplay of factors influencing severe outcomes [19, 20]. Data collection is a critical step in the development of AI models, as the quality and quantity of data directly impact model performance [21, 22]. In this study, data were collected from publicly available sources, including government health agencies, hospitals, and research institutions. The datasets were carefully curated to ensure they were representative of the populations under study. For example, demographic data were obtained from national census reports, while clinical data were collected from electronic health records.

Preprocessing the data is equally important, as raw data often contains errors, missing values, and inconsistencies that can negatively impact model performance [23, 24]. In this study, missing values were handled using imputation techniques, such as mean imputation for numerical data and mode imputation for categorical data. Feature normalization was performed to ensure that all variables were on the same scale, preventing bias in the model. Categorical variables were encoded using one-hot encoding, which converts categorical data into a binary format that can be processed by ML algorithms. The integration of diverse data sources is a key strength of this study, as it enables the models to capture the complex and multifaceted nature of risk factors. For example, demographic data provide insights into population characteristics that may influence disease severity, such as age and ethnicity. Clinical data, such as medical history and laboratory results, provide direct measures of individual health status. Socioeconomic data, including income and housing conditions, provide context for understanding the social determinants of health that may influence disease outcomes.

3.2. Model Development

This study employs supervised ML algorithms, including logistic regression, decision trees, and neural networks, to develop robust risk stratification models [25, 27]. Each algorithm is trained on the preprocessed dataset, and their performance is evaluated using cross-validation to ensure generalizability. Hyperparameter tuning is performed using grid search to optimize model accuracy. The models are designed to predict severe outcomes, such as hospitalization or mortality, during infectious disease outbreaks [26, 28]. The development of supervised ML models involves several steps, including the selection of algorithms, the training of these models, and the evaluation of their performance. In this study, three algorithms were selected: logistic regression, decision trees, and neural networks. These algorithms were chosen for their complementary strengths, with logistic regression providing interpretability, decision trees offering simplicity, and neural networks delivering high accuracy.

Training the models involves fitting them to the preprocessed dataset and optimizing their hyperparameters to achieve the best performance. Hyperparameter tuning is a critical step in model development, as it ensures that the models are well-suited to the specific characteristics of the data. In this study, hyperparameter tuning was performed using grid search, which systematically explores a range of hyperparameter values to identify the optimal combination. Cross-validation was used to assess model performance and prevent overfitting [36, 37]. The final step in model development is the evaluation of the models' performance using metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic (ROC) curve. These metrics provide a comprehensive assessment of model performance, capturing different aspects of predictive accuracy and robustness. For example, accuracy measures the overall correctness of the model's predictions, while precision and recall assess its ability to correctly identify positive cases.

3.3. Model Evaluation

The performance of the supervised ML models is evaluated using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. The models are tested on both historical data and simulated outbreak scenarios to assess their predictive capabilities [34]. Comparative analysis is conducted to evaluate the performance of the supervised ML models against traditional risk stratification methods. The results demonstrate the superiority of the AI-driven approach in identifying high-risk individuals and predicting severe outcomes. Model evaluation is a critical step in the development of AI models, as it provides insights into their performance and reliability. In this study, the supervised ML models were evaluated using a range of metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. These metrics provide a comprehensive assessment of model performance, capturing different aspects of predictive accuracy and robustness. For example, accuracy measures the overall correctness of the model's predictions, while precision and recall assess its ability to correctly identify positive cases.

The models were tested on both historical data and simulated outbreak scenarios to assess their predictive capabilities. Historical data provide a realistic assessment of model performance, as they reflect real-world disease dynamics and challenges. Simulated outbreak scenarios, on the other hand, allow for the evaluation of model performance under controlled conditions, enabling the identification of potential weaknesses and areas for improvement [35]. The results of these tests demonstrated the superior performance of the supervised ML models in predicting severe outcomes.

Comparative analysis was conducted to evaluate the performance of the supervised ML models against traditional risk stratification methods. The results showed that the supervised ML models outperformed traditional methods in terms of accuracy, precision, and recall, highlighting the benefits of the AI-driven approach. This finding is particularly significant, as it demonstrates the potential of supervised ML models to handle the complexity and variability of risk factors, providing more reliable and actionable predictions for healthcare systems.

3.4. Application in Public Health

The developed models are applied to real-world public health challenges, such as identifying high-risk individuals for targeted interventions and optimizing resource allocation during outbreaks [29]. Case studies are presented to illustrate the practical utility of the models in improving health outcomes. For example, the models are used to predict severe outcomes during a simulated influenza outbreak, enabling healthcare providers to prioritize high-risk patients and allocate resources effectively. The application of AI models in public health is a key focus of this study, as it demonstrates the practical utility of these models in addressing real-world challenges [30]. One such challenge is the identification of high-risk individuals for targeted interventions. By predicting the likelihood of severe outcomes in specific individuals, the models enable healthcare providers to prioritize resources and interventions, reducing the overall burden of disease [31]. For example, the models were used to predict severe outcomes during a simulated influenza outbreak, identifying high-risk patients and guiding the allocation of medical supplies and personnel.

Another important application of the models is the optimization of resource allocation during outbreaks. Infectious disease outbreaks often place significant strain on healthcare systems, making it essential to allocate resources efficiently [32]. The models developed in this study provide actionable insights for resource allocation, enabling healthcare providers to prioritize areas with the highest risk of severe outcomes [33]. For example, during a simulated outbreak of COVID-19, the models were used to predict the spread of the disease and guide the allocation of ventilators and intensive care unit (ICU) beds. Case studies are presented to illustrate the practical utility of the models in improving health outcomes [38]. These case studies highlight the ability of the models to provide accurate and timely predictions, enabling healthcare providers to make informed decisions and implement effective interventions. For example, in one case study, the models were used to predict severe outcomes during a dengue fever outbreak, enabling healthcare providers to implement targeted mosquito control measures and reduce disease transmission.

The findings of this study have significant implications for public health practice, as they demonstrate the potential of AI models to enhance risk stratification and outbreak management. By providing accurate and actionable insights, these models enable healthcare providers to make data-driven decisions that improve health outcomes and reduce the impact of infectious disease outbreaks. The application of these models in real-world scenarios highlights their potential to transform public health practice, enabling more effective and equitable responses to infectious disease outbreaks.

3.5. Limitations

Despite the promising results, this study has several limitations that must be addressed in future research. First, the models rely on the availability of high-quality data, which may not always be accessible in low-resource settings. Incomplete or inaccurate data can significantly impact the performance of AI models, leading to unreliable predictions. For example, in regions with limited healthcare infrastructure, clinical data may be incomplete or outdated, reducing the accuracy of risk stratification. Future research should explore alternative data sources, such as mobile health data and community-based surveillance, to address this limitation.

Second, the interpretability of AI models remains a challenge, particularly in the context of public health decision-making. Policymakers and healthcare providers often require transparent and interpretable models to make informed decisions, which can be challenging with complex AI algorithms. Future research should focus on developing interpretable AI models, for example, by using techniques such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to provide insights into model predictions.

Third, the models may struggle to generalize to new or emerging diseases not represented in the training data. Infectious diseases are constantly evolving, with new strains and variants emerging regularly. This poses a challenge for AI models, which are typically trained on historical data and may not be able to accurately predict the behavior of new diseases. Future research should explore transfer learning techniques, which enable models to leverage knowledge from related diseases to improve predictions for new diseases.

Finally, the ethical implications of AI-driven risk stratification must be carefully considered. The use of AI models to prioritize resources and interventions raises important questions about fairness, equity, and privacy. For example, there is a risk that AI models may inadvertently perpetuate existing biases in healthcare, leading to unequal access to resources. Future research should explore ethical frameworks for the use of AI in public health, ensuring that these technologies are used in a way that promotes health equity and protects individual rights.

Recommendations

To enhance the effectiveness of AI-driven risk stratification in public health, the following recommendations are proposed. First, governments and healthcare organizations should prioritize data sharing and collaboration to improve the quality and diversity of datasets. High-quality data are essential for the development of accurate and reliable AI models, and collaboration between stakeholders can help address data gaps and ensure that models are representative of diverse populations and regions. For example, international organizations such as the WHO could facilitate data sharing between countries, enabling the development of global risk stratification models.

Second, investment in computational infrastructure is critical to support the development and deployment of AI models. Many low- and middle-income countries lack the computational resources needed to train and deploy AI models, limiting their ability to benefit from these technologies. International organizations and governments should invest in computational infrastructure, such as cloud computing platforms and high-performance computing clusters, to enable the widespread adoption of AI models in public health.

Third, AI models should be regularly updated with new data to ensure their relevance and accuracy in predicting severe outcomes. Infectious diseases are constantly evolving, and models that are not updated regularly may become outdated and unreliable. Automated pipelines for data collection and model updating should be developed to ensure that models remain accurate and up-to-date. For example, real-time data from wearable devices and social media could be integrated into AI models to provide early warning signs of disease progression.

Finally, interdisciplinary collaboration between data scientists, epidemiologists, and public health policymakers is essential to ensure that AI models are aligned with real-world needs. Data scientists bring technical expertise in AI algorithms and data analysis, while epidemiologists and policymakers provide domain knowledge and insights into public health challenges. Collaborative efforts can help bridge the gap between technical development and practical application, ensuring that AI models are both accurate and actionable. For example, interdisciplinary teams could work together to develop user-friendly interfaces for AI models, enabling policymakers and healthcare providers to easily interpret and act on model predictions.

4. Conclusion

This study demonstrates the potential of AI-driven risk stratification for targeted public health interventions, offering actionable insights for healthcare systems. By leveraging supervised ML algorithms and diverse datasets, the models provide a robust framework for identifying high-risk individuals and predicting severe outcomes during infectious disease outbreaks. The findings highlight the transformative potential of AI in reducing mortality, improving health equity, and enhancing the overall resilience of public health systems. The integration of AI into public health decision-making represents a paradigm shift in how we approach outbreak management. Traditional methods often rely on static risk criteria and historical data, which may not capture the dynamic nature of disease transmission and individual risk profiles. In contrast, AI models can analyze real-time data, identify non-linear relationships, and adapt to changing conditions, enabling more accurate and timely risk stratification. This study contributes to the growing body of knowledge on data-driven public health interventions, providing a foundation for future research and practice.

Despite the promising results, several challenges remain in the application of AI models to public health. These include the availability of high-quality data, the interpretability of AI algorithms, and the ethical implications of AI-driven risk stratification. Addressing these challenges will require continued investment in data infrastructure, computational resources, and interdisciplinary collaboration. Future research should focus on developing innovative solutions to these challenges, enabling the widespread adoption of AI models in public health practice. In conclusion, the development of AI-driven risk stratification models represents a significant advancement in public health research. By providing accurate and actionable insights, these models have the potential to transform public health practice, enabling more effective and equitable responses to infectious disease outbreaks. The findings of this study underscore the importance of continued investment in AI and data-driven approaches to public health, paving the way for a healthier and more resilient future.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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