Streamlining IPAC Surveillance

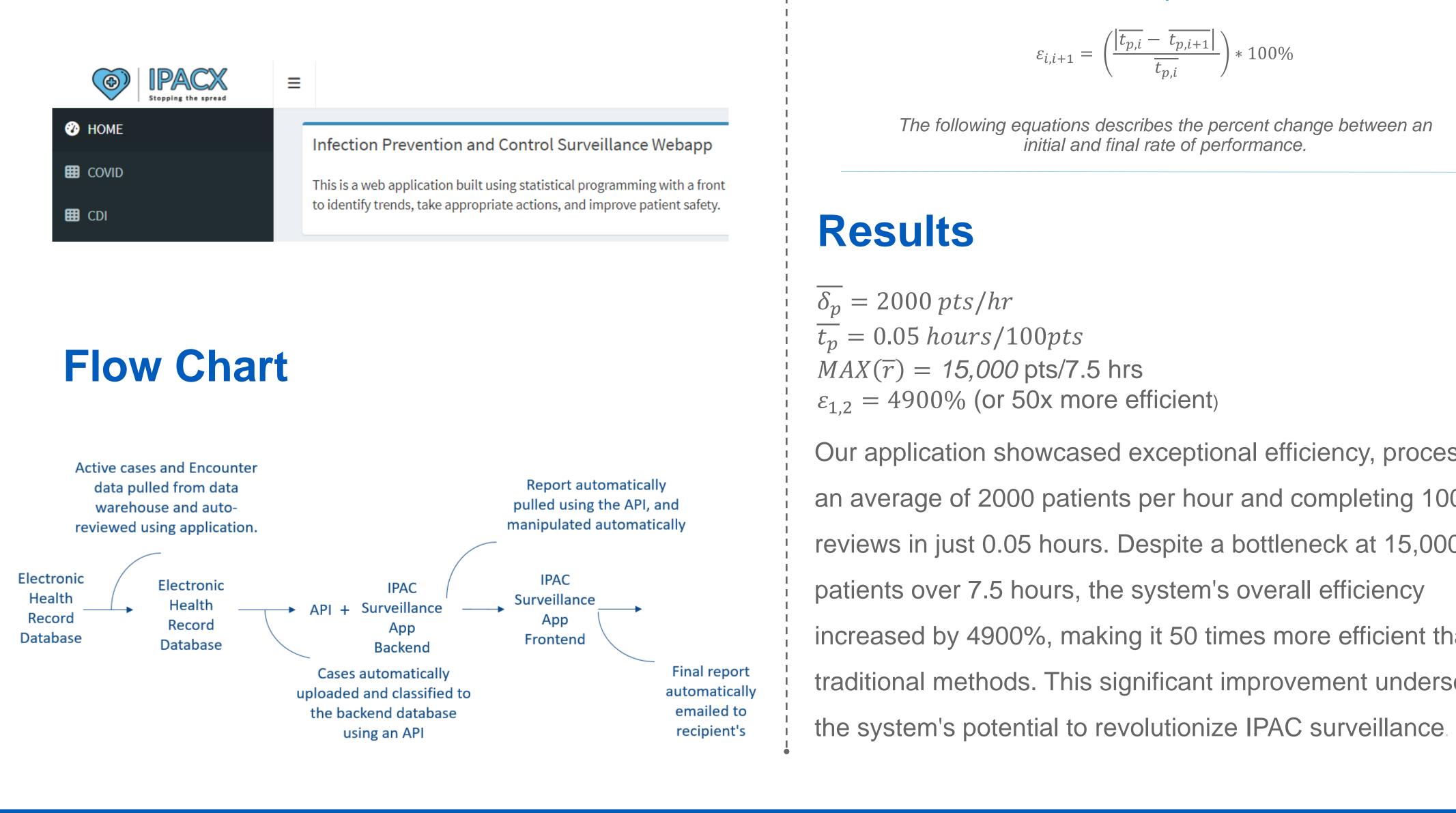
with a Centralized, Customizable, and Interactive Data Platform

Introduction

- Infection Prevention and Control (IPAC) surveillance is essential for reducing healthcare-associated infections [1]
- Manual surveillance practices can be time-consuming, error-prone, and difficult to manage [2]
- Need identified for a centralized repository to integrate data from multiple sources [3]

The Solution

- Web application framework combining statistical programming, intuitive visualizations, and interactive dashboards
- Automatic classification algorithms for identifying healthcare-associated infections
- Customized to the specific needs of the healthcare sector
- Trialed on COVID-19 daily reporting
- Open source/modular framework to extend to all infections type (i.e. CDI, MRSA, ESBL, VRE).



Acknowledgments

We would like to extend our gratitude to the IPAC Department and a special thanks to the REDCap at Island Health team for providing the necessary resources and expertise to implement and optimize the application.

Definitions	
To ensure clarity and facilitate understanding throughout this	Т
report, please reference the key terms below:	COVID Stacke
Average Number of Reviews $\overline{r} = 100 \ (reviews \ per \ day)$	
To accurately compare each of the following methodologies for performance, a standardized Average Number of Reviews per Day will be used.	
$\delta_p = \frac{\sum patient \ Reviews}{time \ to \ complete \ in \ hours}$	Classifi
Rate of patient review refers to the number of patient reviews that can be completed per hour.	his v classi
Average Patient Review Rate $\overline{\delta_p} = \frac{\sum \delta_p}{5 \ days}$	and a the 'tr
The average patient review rate is calculated by taking the sum of 1 work week of δ_p patient review rates and dividing by 5 days (1 work week).	COVID Rates Plo
Time of completion	4.0-
$\overline{t_p} = \frac{\overline{r}}{\overline{\delta_p}}$	3.5-
The following equation calculates the time required to complete \bar{r} (100 reviews). Where $\overline{\delta_p}$ refers to the average patient review rate.	2.5-
Percent Improvement	
$\varepsilon_{i,i+1} = \left(\frac{\left \overline{t_{p,i}} - \overline{t_{p,i+1}}\right }{\overline{t_{p,i}}}\right) * 100\%$	This li COVI
The following equations describes the percent change between an initial and final rate of performance.	i numb target monit
Results	trends
$\overline{\delta_p} = 2000 \ pts/hr$ $\overline{t_p} = 0.05 \ hours/100 \ pts$ $MAX(\overline{r}) = 15,000 \ pts/7.5 \ hrs$ $\varepsilon_{1,2} = 4900\% \ (or \ 50x \ more \ efficient)$	COVID Biobu
Our application showcased exceptional efficiency, processing	-0-
an average of 2000 patients per hour and completing 100	I Classif
reviews in just 0.05 hours. Despite a bottleneck at 15,000	
patients over 7.5 hours, the system's overall efficiency	This b classi
increased by 4900%, making it 50 times more efficient than	i Cases
traditional methods. This significant improvement underscores	overvi

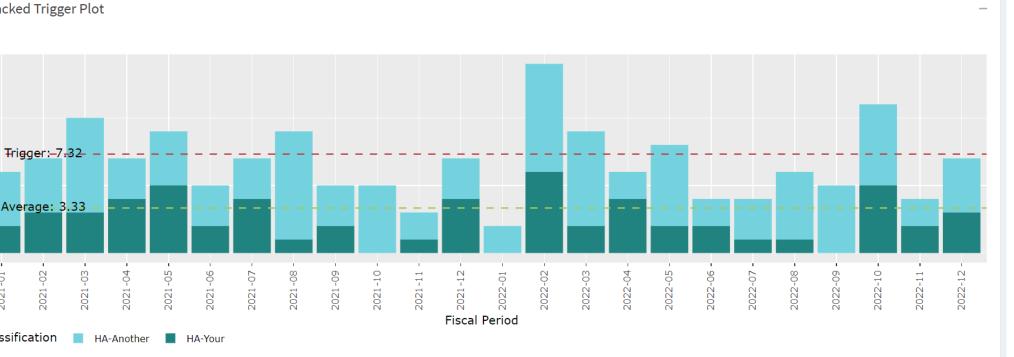
Authors

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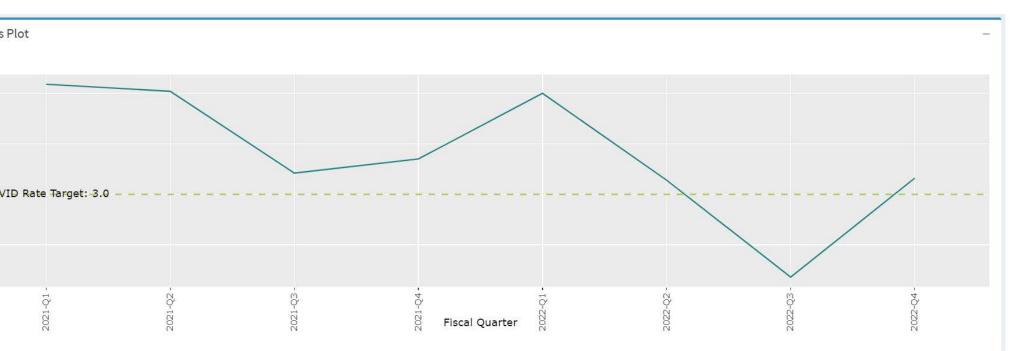


Data Visualization

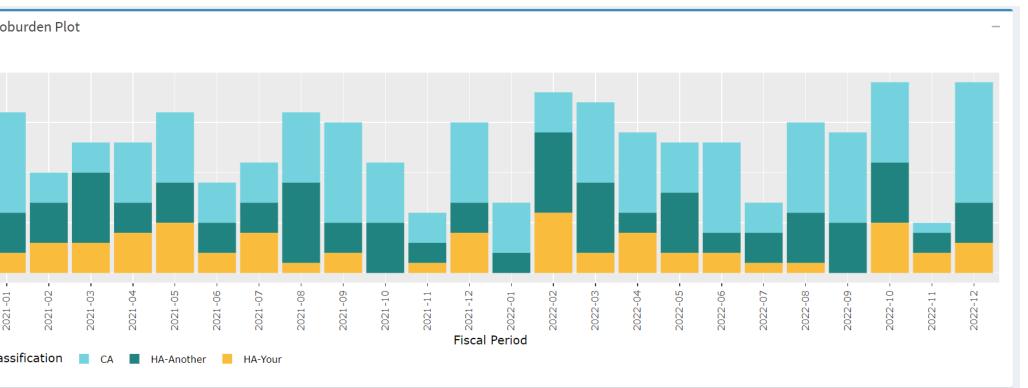
The data visualizations below are meant to demonstrate the potential of this system but do not include any real patient or surveillance data.



visualization provides a summary of infection cases by fiscal period and sification. It shows the number of cases in each fiscal period, differentiated by ification type. Two horizontal dashed lines represent the average number of cases calculated 'trigger' value. The average line gives a baseline for comparison, while rigger' line, calculated as two standard deviations above the average, indicates a ntial alert level for unusually high case numbers.



line graph illustrates the rate of healthcare associated infections (in this case (ID-19) cases per fiscal quarter. The y-axis shows the calculated rate, which is the per of cases per 10,000 patient-days. A horizontal dashed line represents the rate of 3.0, providing a reference point for comparison. This visualization helps in toring the progress of the infection rate over time, facilitating the identification of s and the evaluation of infection control measures.



bar chart presents the number of collected COVID-19 cases by fiscal period and ification. Each bar represents a fiscal period, and the height indicates the number of . Different classifications are represented by different colors, providing a clear visual overview of case distribution. This visualization serves as a tool to monitor the 'bioburden', or the number of infectious agents, at different time points, aiding in evaluating the burden of disease over time.

Findings

Our investigation revealed that the automated surveillance system significantly contributed to the enhancement of IPAC surveillance and optimization of data management procedures. The design, which focuses on flexibility, is particularly well-tailored to the fluctuating demands of the healthcare sector. Encapsulated within a user-friendly interface, the automated procedure utilizes an advanced algorithm to maintain consistent performance and support automatic case classification.

The application's open-source functionality stimulates innovation and broad customization, potentially reshaping IPAC practices. Its adaptable structure allows expansion to monitor various infections such as CDI, MRSA, ESBL, VRE, SSIs, Influenza, and RSV. Notably, it's applicable in both acute and long-term care facilities.

Across all infections, the application consistently improved data efficiency, accuracy, and transparency. Customizable data visualization enabled swift trend identification, infection rate tracking, and evidence-based prevention decisions. These results highlight the application's potential as a comprehensive IPAC surveillance tool, transforming data management across diverse infectious diseases.

Conclusion

Overall, our study demonstrates the potential of our application to support IPAC surveillance and data management practices. By consolidating and standardizing IPAC surveillance tools into a single platform, we can help reduce the risk of errors and better support staff, promoting patient safety, with well-informed decision-making. Our results highlight the benefits of customizing data visualization programs to meet the specific needs of the healthcare sector, and our approach can be applied to other IPAC surveillance initiatives and data management practices.

References

1.IPAC surveillance is essential for reducing healthcare-associated infections (World Health Organization, 2020). 2.Manual surveillance can be error-prone and difficult to manage (Woeltje et al., 2008). 3.A centralized repository is necessary to integrate data from multiple sources (Safran et al., 2007).

