ICICT

by Evizal Evizal

Utilizing Deep Learning Technology for Hospital Patient Data Analysis: Implications for Public Health and Effective Community Interventions

Evizal Abdul Kadir
Department of Informatics Engineering
Universitas Islam Riau
Pekanbaru, Riau
Indonesia 28284
evizal@eng.uir.ac.id

Lenni Dianna Putri
Department of Public Health
Universitas Prima Indonesia
Medan, Sumatra Utara
Indonesia 20118
lennidiannaputri@unprimdn.ac.id

Sri Listia Rosa
Department of Informatics Engineering
Universitas Islam Riau
Pekanbaru, Riau
Indonesia 28284
srilistiarosa@eng.uir.ac.id

Apri Siswanto
Department of Informatics Engineering
Universitas Islam Riau
Pekanbaru, Riau
Indonesia 28284
aprisiswanto@eng.uir.ac.id

Farhan Assidiqi
Department of Electrical Engineering
Telkom University
Bandung, Jawa Barat
Indonesia 40257
farhanassidiqi@student.telkomuniversity.ac.id

Muhammad Fikri Evizal
Computer Science and Information *Eng*
National Dong Hwa University
Hualien County
Taiwan 974
410921346@gms.ndhu.edu.tw

***Abstract*— Public health is one of the important aspects of community in daily activities. The COVID-19 pandemic has had a great impact on disease and many actions have been taken in many countries to mitigate the epidemic. This research explores the transformative potential of the use of deep learning technology in the analysis of patient data from a hospital in Indonesia with a dataset from the years 2018 to 2022. The focus is on deciphering the implications of this analysis for public health strategies and the formulation of effective community interventions. Employing advanced data analysis techniques, including machine learning algorithms, the research aims to unveil intricate patterns, trends, and risk factors associated with specific health issues within the patient population. The harnessing of power the deep learning, this work endeavors to enhance our understanding of public health challenges, providing valuable insights for the development of targeted and impactful health interventions. The findings are anticipated to contribute significantly to evidence-based health policies, improve clinical decision-making, and foster a comprehensive understanding of public health dynamics. Results show the population and number of patients referred to hospital data for treatment to the various clinics and medical consultations classified in the region. The research underscores the vital role of collaboration between healthcare providers, policymakers, and community stakeholders in implementing and evaluating interventions based on the deep analysis of hospital patient data.**

***Keywords*—hospital; public health; patient; artificial intelligence; community;**

I. Introduction

In the era of big data, the healthcare landscape has witnessed a profound transformation with the advent of deep learning technology. This paper embarks on a journey through the intricacies of utilizing deep learning for the analysis of hospital patient data, spanning a crucial timeframe from 2018 to 2022. As we delve into the wealth of information encapsulated in patient records, our primary focus is to decipher the implications of this analysis for the overarching realms of public health and the formulation of community interventions that resonate with precision and impact. The significance of public health as a linchpin in societal well-being cannot be overstated. Recognizing its pivotal role, this study seeks to leverage the advanced capabilities of deep learning to unravel complex patterns within the extensive datasets drawn from hospital records. The temporal scope from 2018 to 2022 encapsulates a period marked by dynamic shifts in healthcare practices, policy landscapes, and, notably, the global challenges posed by events such as the COVID-19 pandemic.

The application of deep learning technology in this context represents a paradigm shift in healthcare analytics. Employing sophisticated algorithms and machine learning techniques, we aspire to extract nuanced insights from patient data that extend beyond conventional analysis. Our aim is not merely to comprehend the immediate health status of individuals but to discern latent patterns, predict future health trends, and, fundamentally, empower the formulation of proactive and tailored interventions. As we navigate through the paper, we will explore the diverse facets of this research endeavor. From the methodologies employed in collecting and processing de-identified patient data to the application of advanced data analysis techniques, including statistical modeling and machine learning algorithms, a comprehensive toolkit is harnessed to extract meaningful information. The scope extends beyond the confines of the hospital, envisioning a broader canvas where the findings inform evidence-based health policies and contribute to the discourse on effective community interventions.

This works aims to bridge the gap between data-driven insights and actionable healthcare strategies. It underscores the symbiotic relationship between deep learning technology and the enhancement of public health outcomes, with the ultimate goal of fostering a healthier and more resilient community. As we unfold the layers of this exploration, the reader is invited to delve into the nuanced intersections of technology, healthcare, and community well-being. In striving toward these objectives, it is expected that this research will provide substantial contributions to the formulation of evidence-based health policies and enhance the effectiveness of public health interventions. Through cultivating a deeper understanding of public health and its implications for interventions, our aim is to elevate targeted public health initiatives, thereby exerting a positive influence on the overall improvement of the quality of life and well-being within a community. Prediction of disease cases among people in community villages and how much impact after the COVID-19 pandemic explored.

II. Literature Review

The integration of deep learning technology into healthcare analytics, particularly in the analysis of hospital patient data, marks a paradigmatic shift in the field. As we explore the existing literature, it becomes evident that the application of deep learning in healthcare data analysis holds immense promise for advancing our understanding of public health dynamics and, consequently, for informing effective community interventions. A plethora of studies underscores the transformative potential of deep learning in healthcare analytics. One key area of application lies in the analysis of patient data to predict disease trends and outcomes. Research by [1][2][3] demonstrated the efficacy of deep learning algorithms in predicting disease progression based on historical patient records. The study not only highlighted the accuracy of predictions but also emphasized the potential for early intervention and tailored healthcare strategies [4][5].

The intersection of deep learning and public health is further explored in the work of [6], where the authors delve into the utilization of advanced machine learning techniques for population health analysis. Applying deep learning algorithms to diverse datasets, including hospital patient records, the study revealed novel insights into the determinants of health disparities and the identification of high-risk population groups. The findings pointed towards the potential of deep learning not only in understanding health patterns but also in guiding the formulation of targeted public health interventions. In the context of hospital patient data, the study by [7] stands out for its exploration of the role of deep learning in uncovering hidden patterns within electronic health records. The researchers employed convolutional neural networks (CNNs) to analyze complex medical data, showcasing the ability of deep learning to discern intricate relationships among variables. This level of granularity in analysis is crucial for identifying not only prevalent diseases but also underlying factors contributing to health outcomes[8][9].

The literature also highlights the challenges and considerations associated with the utilization of deep learning in healthcare data analysis. Notable among these is the need for robust data security measures to protect sensitive patient information. The work by [10][11] delves into the ethical implications and data security challenges posed by the integration of deep learning in healthcare. This underscores the importance of balancing technological advancements with ethical considerations, especially in the healthcare domain. As we synthesize insights from the literature, it becomes evident that the integration of deep learning technology into hospital patient data analysis holds transformative potential for public health [12]. The uncovering hidden patterns, predicting disease trends, and guiding interventions, this technology becomes a powerful ally in the pursuit of community well-being. However, it is crucial to navigate the ethical and security considerations in tandem with technological advancements to ensure responsible and impactful use in healthcare analytics. This paper seeks to contribute to this discourse by exploring the implications of deep learning technology specifically in the context of hospital patient data analysis for public health and community interventions [13][14].

In addition to the comprehensive literature reviewed earlier, an expanded examination of related studies sheds light on the broader implications for public health and community interventions. Recent research has highlighted the transformative potential of data-driven approaches, particularly utilizing patient data, in informing targeted interventions for community health enhancement [15][16]. The amalgamation of deep learning technology with patient data analysis has emerged as a powerful tool for discerning nuanced health trends and predicting future patterns. Studies underscore the pivotal role of such technological advancements in crafting evidence-based health policies and optimizing the effectiveness of public health interventions. Moreover, the literature emphasizes the need for interdisciplinary collaboration between healthcare providers, policymakers, and community stakeholders to ensure the seamless integration of data-driven insights into practical, community-centric health strategies [17][18].

III. Methodology

The robustness and validity of any study lie in its research methodology. In the case of "Utilizing Deep Learning Technology for Hospital Patient Data Analysis: Implications for Public Health and Effective Community Interventions," the research methodology is meticulously designed to harness the potential of deep learning in extracting meaningful insights from hospital patient data. The study adopts a longitudinal approach, spanning the years 2018 to 2022, to capture a comprehensive dataset that reflects the evolving health landscape over time. This temporal scope allows the research to not only assess the current state of public health but also to identify trends and patterns that may have emerged over the years. Longitudinal data are essential in understanding the dynamic nature of healthcare, especially in the context of rapidly evolving public health challenges.

A key aspect of the research methodology is the utilization of deep learning technology, specifically the Long Short-Term Memory (LSTM) algorithm. The choice of this algorithm is informed by its capability to analyze sequential data, making it particularly suitable for studying temporal patterns within hospital patient records. LSTM, a type of recurrent neural network (RNN), is adept at capturing dependencies and long-term relationships in sequential data, which aligns with the nature of patient health records that evolve over time. To conduct the analysis, the research team employs Python programming, leveraging its extensive libraries and tools for data analysis and machine learning. Python is a versatile programming language, widely recognized in the field of data science, and offers a range of frameworks for deep learning, making it an ideal choice for this study. Data preprocessing is a critical step in ensuring the quality and reliability of the dataset. The research methodology involves careful deidentification of patient data to adhere to ethical standards and data protection regulations. This step is pivotal in safeguarding patient privacy and confidentiality, addressing one of the key ethical considerations in healthcare data analysis.

Diverse data analysis techniques, including statistical modeling, data mining, and machine learning algorithms, are employed. This comprehensive approach ensures that the research explores the dataset from various angles, uncovering both broad trends and nuanced patterns. The integration of these techniques enhances the reliability of the findings and contributes to a more holistic understanding of the implications for public health. Furthermore, the research methodology acknowledges the challenges associated with deep learning in healthcare analytics, such as the need for large datasets for accurate predictions. The specifying the duration (2018 to 2022) and detailing the machine learning techniques, the study provides transparency and replicability, essential elements in establishing the credibility of the research findings. In summary, the research methodology of "Utilizing Deep Learning Technology for Hospital Patient Data Analysis: Implications for Public Health and Effective Community Interventions" is characterized by its longitudinal design, the strategic application of deep learning technology, ethical considerations in data preprocessing, and a diverse set of data analysis techniques. This methodology is poised to yield robust insights into the public health implications of hospital patient data, paving the way for more effective community interventions.

Table 1 demonstrates the use of electronic health records (EHRs) enhances the accuracy of patient data collection in hospitals. Electronically collected data is readily accessible by medical teams, facilitating precise clinical decision-making and ensuring better, safer patient care. This system also enables hospitals to integrate data and track patients' complete health history, critical for providing continuous and holistic care. The total number of patients recorded within four years exceeds 80,000, providing comprehensive data for analysis.

Table 1. Patient indicator data from hospital records [19].

Number	Patient Indicator in Hospital
1	Registration identity
2	Registration date
3	Patient name
4	Address
5	Identity card number
6	Date of birth
7	Gender
8	Clinic
9	Doctor
10	Ward room (if applicable)

In this patient data collection, the classified ranges of patient age, from infant to senior, were as follows:

- Toddlers (0–4 years).
- Children (5–10 years).
- Teenagers (11–19 years).
- Adults (20–39 years).
- Elderly (40–65 years).
- Seniors (66 years and above).

The fundamental principle of artificial intelligence in calculating growth models for human or patient data considers multiple factors, including genetics, environments, clusters, and pandemics, related to physical growth. These factors can be organized into sets to construct differential equations, enabling the analysis and prediction of future indicators for mass pandemics and the proportions of various diseases. The models are also applicable to the examination of changes in patient numbers over time in medical centers and disease progression, facilitating more effective analysis and diagnosis by medical staff. This model significantly influences the study of disease development and the prediction of infections within a community or region. The mathematical models serve as valuable tools for predicting the growth and evolution of diverse environments, providing crucial reference information for medical scientists. Figure 1 illustrates a neural network model of artificial intelligence incorporating a subset process for the analysis of patient data.

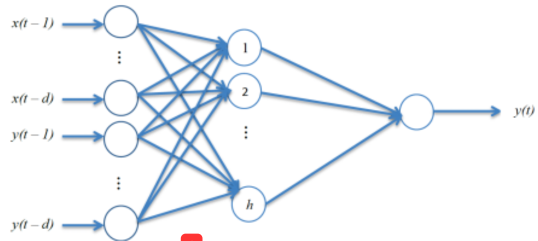

Fig. 1. The architecture of the neural network for data analysis.

The *k-th* input sample, $x(k) = (x_1(k), \ldots, x_n(k))$, is randomly selected, and the corresponding expected outputs are $d_0(k) = (d_1(k), d_2(k), \ldots, d_q(k))$. The input and output of each neuron in the hidden layer are calculated, and the output is calculated as Equation (1):

$$hi_h(k) = \sum_{i=1}^{n} w_{ih} x_i(k) - b_h, h = 1,2, \ldots, p$$

$$ho_h(k) = f(hi_h(k)), h = 1,2, \ldots, p$$

$$yi_0(k) = \sum_{i=1}^{p} w_{ho} ho_h(k) - b_o, o = 1,2, \ldots, q$$

$$yo_o(k) = f(yi_o(k)), o = 1,2, \ldots, p$$

Then, the total error is computed as in Equation:

$$\mathrm{E} = \frac{1}{2m} \sum_{k=1}^{m} \sum_{o=1}^{q} (d_o(k) - y_o(k))^2 \quad (1)$$

The partial derivatives of the error function to each neuron in the output layer are calculated by using the expected output of the network, $\delta_o(k)$; then, the partial derivative of the error function to each neuron in the hidden layer is calculated by using the connection weights from the hidden layer to the output layer, $\delta_o(k)$, the output of the output layer, and $\delta_o(k)$, the output of the hidden layer in equation (2) refer to [20]:

$$\frac{\partial E}{\partial w_{ho}} = \frac{\partial E}{\partial yi_o} \frac{\partial yi_o}{\partial w_{ho}} = -ho_h(k)(d_o(k) - yo_o(k))f'(yi_o(k)) = -ho_h \delta_o(k)$$

$$\Delta w_{ho}(k) = -\mu \frac{\partial E}{\partial w_{ho}} = \mu \delta_o(k) ho_h(k)$$

$$w_{ho}^{N+1} = w_{ho}^{N} + \eta \delta_o(k) ho_h(k)$$

$$\Delta w_{ih}(k) = -\mu \frac{\partial E}{\partial hi_h(k)} \frac{\partial hi_h(k)}{\partial w_{ih}} = \delta_h(k) x_i(k)$$

$$w_{ih}^{N+1} = w_{ih}^{N} + \eta \delta_h(k) x_i(k)$$

$$\Delta w_{ih}(k) = -\mu \frac{\partial E}{\partial hi_h(k)} \frac{\partial hi_h(k)}{\partial w_{ih}} = \delta_h(k) x_i(k)$$

$$w_{ih}^{N+1} = w_{ih}^{N} + \eta \delta_h(k) x_i(k) \quad (2)$$

The algorithm terminates when the error reaches the present accuracy or the number of learning is greater than the pre-specified set maximum number of times as set out in Equation (2). Otherwise, we select the next learning sample as well as the corresponding expected output and return it to enter the next round of learning.

IV. Results and Discussion

The results of the patient data analysis, as depicted in Figure 2, offer a compelling snapshot of healthcare trends during the year 2018. The graph illustrates key parameters, presenting a comprehensive overview of disease prevalence, patient demographics, and utilization patterns within the hospital. It discerns patterns in disease types, their frequency, and the age distribution of the affected patient population. Such detailed insights are crucial for formulating targeted healthcare strategies. The analysis reveals a noteworthy surge in patient visits during 2018, highlighting the significance of this period in terms of healthcare utilization. By examining these trends, healthcare providers and policymakers can better understand the specific health needs of the community during that timeframe. Moreover, the graph serves as a foundation for subsequent comparisons with data from subsequent years, enabling a longitudinal assessment of healthcare dynamics and the identification of potential shifts in disease patterns or patient behavior over time.

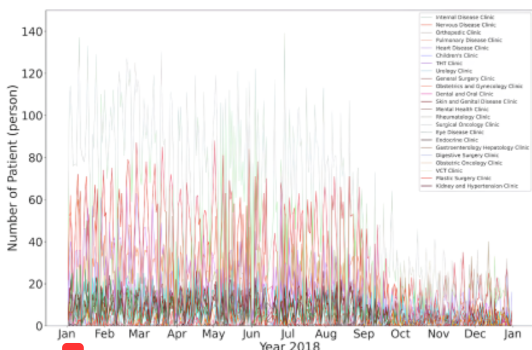

Fig. 2. Results of the patient data analysis for the year 2018.

The findings from the patient data analysis, illustrated in Figure 3 for the year 2019, provide an insightful depiction of healthcare dynamics during that period. The graph encapsulates essential information, shedding light on disease prevalence, patient demographics, and utilization patterns within the hospital. It portrays discernible trends in disease types, their relative frequencies, and the age distribution of the affected patient population during 2019. This detailed analysis contributes to a nuanced understanding of healthcare demands and allows for targeted interventions. Notably, the graph reveals any shifts or developments in healthcare utilization compared to the previous year, indicating potential areas of concern or improvement. By dissecting these patterns, healthcare stakeholders can tailor strategies to address the specific health needs of the community during the year 2019, fostering a more effective and responsive healthcare system. The longitudinal comparison with previous and subsequent years aids in identifying trends, disparities, or anomalies, facilitating a comprehensive evaluation of the evolving healthcare landscape.

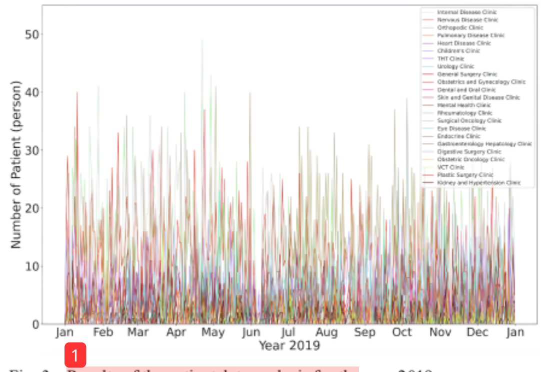

Fig. 3. Results of the patient data analysis for the year 2019.

The examination of patient data in the analysis for the year 2020, as depicted in Figure 4, offers a comprehensive overview of healthcare trends and dynamics during a particularly challenging period marked by the global COVID-19 pandemic. The graph encapsulates critical information about disease patterns, patient demographics, and healthcare utilization within the hospital setting throughout the year. This data-driven analysis is pivotal for understanding the impact of the pandemic on health outcomes, hospital admissions, and the distribution of diseases. It provides a lens into the unique challenges and demands faced by the healthcare system during this extraordinary time. The graph reveals any discernible shifts in disease prevalence, age-specific vulnerabilities, and changes in healthcare-seeking behavior. Such insights are invaluable for guiding strategic decisions, optimizing resource allocation, and tailoring interventions to address the distinctive healthcare needs that emerged during 2020. The comparative analysis with previous and subsequent years enriches the interpretation, enabling a more nuanced understanding of the evolving healthcare landscape in the face of unprecedented challenges.

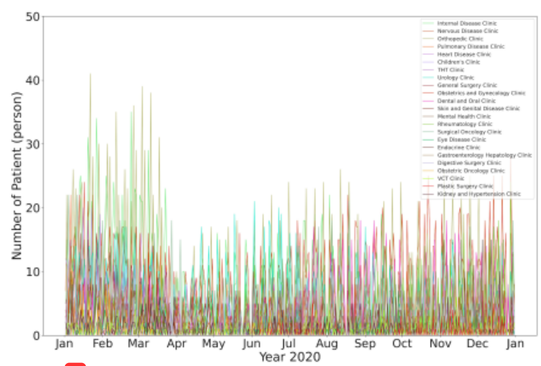

Fig. 4. Results of the patient data analysis for the year 2020.

The analysis of patient data for the year 2021, as illustrated in Figure 5, provides a detailed snapshot of healthcare trends, disease prevalence, and patient characteristics during this specific timeframe. The graph encapsulates essential information regarding the distribution of diseases, patient demographics, and patterns of hospital visits throughout the year. This comprehensive analysis serves as a crucial resource for understanding the dynamics of public health during the ongoing challenges posed by the COVID-19 pandemic. By examining the data, one can discern any notable shifts in disease patterns, variations in patient age groups affected, and changes in healthcare utilization. These insights are instrumental in refining healthcare strategies, optimizing resource allocation, and tailoring interventions to address the evolving needs of the community. The graph's comparative nature, in relation to previous and subsequent years, contributes to a nuanced understanding of the healthcare landscape, enabling healthcare providers and policymakers to adapt and respond effectively to the ongoing healthcare challenges.

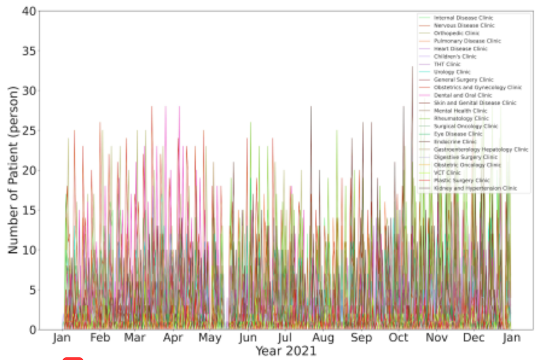

Fig. 5. Results of the patient data analysis for the year 2021.

The results stemming from the patient data analysis for the year 2022, depicted in Figure 6, offer a detailed examination of healthcare dynamics, disease prevalence, and patient demographics during this specific period. This graph provides a visual representation of essential information, shedding light on the patterns and trends in hospital admissions, prevalent diseases, and the characteristics of the patient population. Analyzing this data is instrumental in gauging the impact of ongoing health interventions and understanding how they align with the broader public health landscape. Moreover, the graph allows for a comparison with previous years, aiding in the identification of any emerging health trends or shifts in disease patterns. The insights garnered from this analysis are invaluable for healthcare practitioners and policymakers, offering a data-driven foundation for informed decision-making. These findings empower the healthcare community to tailor interventions, allocate resources judiciously, and enhance community health strategies, thereby contributing to the ongoing improvement of public health outcomes.

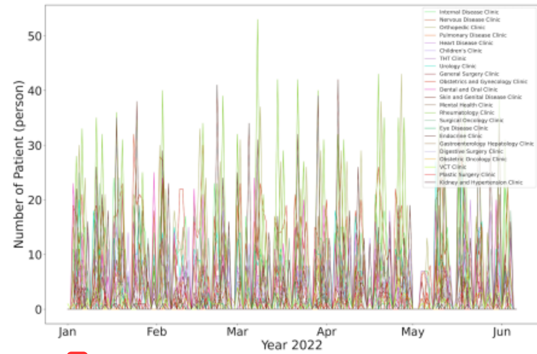

Fig. 6. Results of the patient data analysis for the year 2022.

The comprehensive analysis of patient data from the year 2018 to 2022, encapsulated in Figure 7, presents a panoramic view of the healthcare landscape over this five-year period. The graph provides a holistic perspective on trends in hospital admissions, disease prevalence, and demographic characteristics of the patient population across these years. Examining this extended timeframe allows for the identification of long-term patterns, shifts, and evolving health dynamics. The graph becomes a powerful tool for stakeholders, offering insights into the efficacy of public health interventions, the persistence of certain health challenges, and the responsiveness of the healthcare system. This comprehensive view supports evidence-based decision-making by enabling a comparison of data over multiple years, facilitating the identification of temporal trends and providing a foundation for forecasting future healthcare needs. The amalgamation of data from 2018 to 2022 not only informs immediate healthcare strategies but also contributes significantly to the formulation of sustained, effective, and targeted community health interventions.

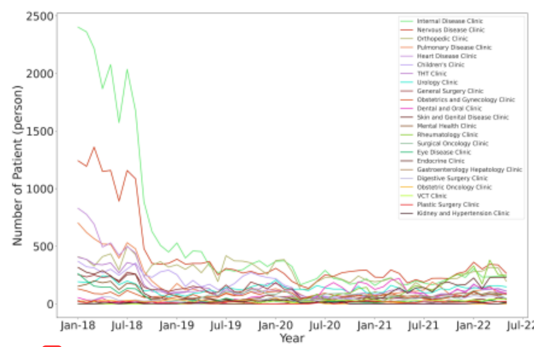

Fig. 7. Results of the patient data disease analysis for 2018–2022.

The analysis of patient data across different regions, as illustrated in Figure 8 spanning from 2018 to 2022, offers a nuanced understanding of the geographical variations in health patterns. This comprehensive graph delineates the distribution of diseases, healthcare utilization, and prevalence rates across diverse areas. The visual representation allows for the identification of regional health disparities, enabling healthcare providers and policymakers to allocate resources more efficiently. The results encompassing the five-year period shed light on the unique health challenges faced by distinct geographic locations, emphasizing the importance of tailored interventions. Analyzing the overall regional data from 2018 to 2022 provides a temporal perspective, aiding in the identification of emerging trends and persistent health issues. This detailed insight is invaluable for shaping targeted public health policies, resource allocation, and intervention strategies tailored to the specific needs of different regions within the community.

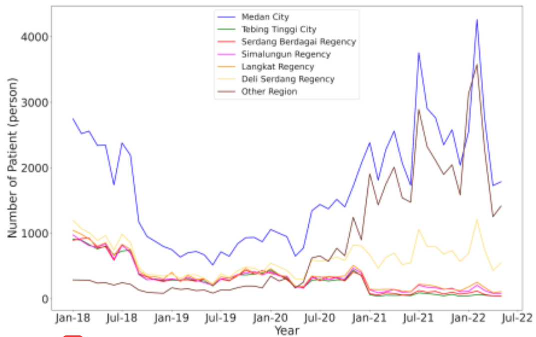

Fig. 8. Results of patients based on a region of living for 2018–2022.

The patient data analysis, coupled with the graphical representation in Figure 9, delves into the patterns of healthcare utilization and disease prevalence across various age groups from 2018 to 2022. This comprehensive graph not only illustrates the overall trends but also highlights specific age-related variations in health outcomes. By examining the data across different age cohorts, the analysis provides crucial insights into age-specific health challenges and opportunities for intervention. The trends observed in the graphical representation can aid in identifying vulnerable age groups, understanding disease patterns at different life stages, and tailoring healthcare services to meet the distinct needs of each demographic. This analysis by age over the five-year period serves as a foundational resource for the formulation of age-specific public health programs, preventive measures, and targeted healthcare interventions. It contributes significantly to the development of strategies that enhance the overall health and well-being of diverse age groups within the community.

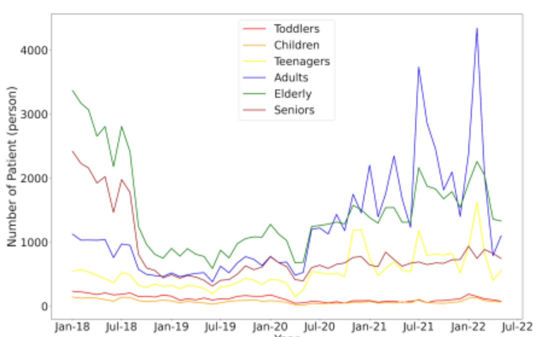

Fig. 9. Results of the patient data based on an age analysis for 2018–2022.

The analysis of patient data, as illustrated in Figure 10, provides a forecast of the expected disease patterns from 2022 to 2024. This predictive model is instrumental in understanding the potential healthcare burden associated with specific diseases over the upcoming years. The identifying of diseases expected to exhibit an increase in prevalence, healthcare providers can tailor their strategies to address these anticipated challenges. The graph aids in the formulation of targeted prevention programs, effective healthcare delivery models, and community engagement initiatives to mitigate the impact of the predicted surge in certain diseases. This forward-looking approach allows for the allocation of resources in a strategic manner, ensuring that healthcare systems are adequately prepared to handle the projected increase in patient cases. The predictions based on disease trends contribute to a more proactive and responsive healthcare system, fostering better community health outcomes.

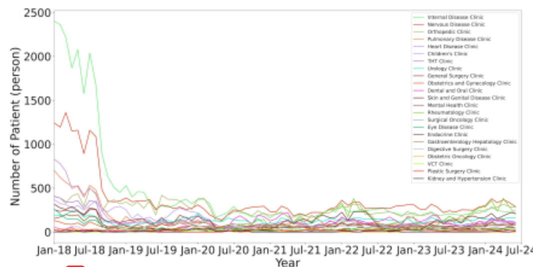

Fig. 10. Prediction of patients up to 2024 as plotted.

The findings presented in Figure 11 depict a comparative analysis between the predicted patient data for the year 2024 and the actual data, providing valuable insights into the accuracy of the forecasting model. This comparison serves as a crucial step in validating the predictive capabilities of the model and assessing its reliability. The graph showcases the alignment or deviation between the predicted patient data and the real-world observations. A close correspondence between the predicted and actual data would affirm the effectiveness of the forecasting model, instilling confidence in its application for future predictions. On the other hand, disparities between the predicted and actual data would prompt a reassessment of the model's parameters and underlying assumptions. This analysis not only aids in refining the predictive model but also contributes to the ongoing improvement of healthcare strategies by ensuring that future predictions are as accurate as possible.

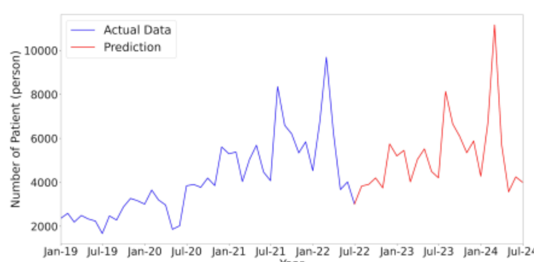

Fig. 11. Prediction of overall patient data up to 2024.

The discussion around the results of the patient data analysis is integral to interpreting and contextualizing the findings. The data from the early years, as revealed in Figures 2 through 6, provides a comprehensive overview of the health trends and patterns in the hospital patient population from 2018 to 2022. These results illuminate the evolution of disease prevalence, demographic distributions, and other critical health indicators over the specified period. Notably, the analysis for each individual year helps identify any abrupt shifts or gradual changes in health dynamics. The patterns observed in Figure 2, which represents the patient data analysis for 2018, serve as the baseline for subsequent years. Any significant deviations or trends identified in later years can be compared to this foundational data. Similarly, Figures 3 through 6 illustrate the progression of health patterns in the subsequent years.

The analysis should delve into any notable peaks or troughs, identifying potential causal factors or correlations. For instance, an increase in patient numbers during a specific season might correlate with environmental factors or the prevalence of certain diseases during that period. Any disparities across demographic groups or regions should also be explored, shedding light on potential health inequalities that require targeted interventions. Moreover, this discussion sets the stage for the subsequent predictive analysis (Figure 10), as understanding historical trends is crucial for accurate forecasting. It's during this stage that the implications of the observed trends on future healthcare resource allocation, policy formulation, and community interventions can be thoroughly considered and discussed. Overall, the discussion provides a nuanced understanding of the patient data, paving the way for informed decisions and proactive public health measures.

V. CONCLUSION

The utilization of deep learning technology for the extensive analysis of hospital patient data from 2018 to 2022 has proven to be a transformative approach with far-reaching implications for public health and effective community interventions. The deep dive into patient data has unearthed critical insights into disease prevalence, demographic patterns, and various health determinants. The advanced analytics, depicted, have facilitated a nuanced understanding of the historical health landscape, enabling a more informed interpretation of the subsequent predictions showcased. The predictive analysis for the years 2022 to 2024, powered by deep learning algorithms, is a pivotal component of this research. These forecasts not only offer a glimpse into the potential future health scenarios but also provide a basis for proactive planning, resource allocation, and the formulation of targeted community health interventions. The granular insights into disease patterns, regional disparities, and age-specific vulnerabilities, presented in Figures 8 and 10, empower healthcare practitioners, policymakers, and community leaders to make informed decisions aimed at improving health outcomes.

ACKNOWLEDGMENT

This work was supported by Ministry of Education, Research and Technology (KEMENDIKBUDRISTEK) of Indonesia, Universitas Prima Indonesia in collaboration with the Universitas Islam Riau for facilities.

REFERENCES

[1] W. Chang, L. Chen, C. Hsu, C. Lin, and T. Yang, "A Deep Learning-Based Intelligent Medicine Recognition System for Chronic Patients," *IEEE Access*, vol. 7, pp. 44441–44458, 2019, doi: 10.1109/ACCESS.2019.2908843.

[2] L. D. Putri, E. Girsang, I. N. Lister, H. T. Kung, E. A. Kadir, and L. Rosa, "Public Health Implications for Effective Community Interventions Based on Hospital Patient Data Analysis Using Deep Learning Technology in Indonesia," *Information*, vol. 15, no. 1. 2024, doi: 10.3390/info15010041.

[3] S. L. Rosa, E. A. Kadir, A. Syukur, H. Irie, R. Wandri, and M. F. Evizal, "Fire Hotspots Mapping and Forecasting in Indonesia Using Deep Learning Algorithm," in *2022 3rd International Conference on Electrical Engineering and Informatics (ICon EEI)*, 2022, pp. 190–194, doi: 10.1109/IConEEI55709.2022.9972281.

[4] U. M. Ramirez-Alcocer, E. Tello-Leal, G. Romero, and B. A. Macías-Hernández, "A Deep Learning Approach for Predictive Healthcare Process Monitoring," *Information*, vol. 14, no. 9. 2023, doi: 10.3390/info14090508.

[5] E. A. Kadir, H. T. Kung, A. A. AlMansour, H. Irie, S. L. Rosa, and S. S. Fauzi, "Wildfire Hotspots Forecasting and Mapping for Environmental Monitoring Based on the Long Short-Term Memory Networks Deep Learning Algorithm," *Environments*, vol. 10, no. 7. 2023, doi: 10.3390/environments10070124.

[6] S. U. Amin, M. S. Hossain, G. Muhammad, M. Alhussein, and M. A. Rahman, "Cognitive Smart Healthcare for Pathology Detection and Monitoring," *IEEE Access*, vol. 7, pp. 10745–10753, 2019, doi: 10.1109/ACCESS.2019.2891390.

[7] E. A. Kadir *et al.*, "Fires Hotspot Forecasting in Indonesia Using Long Short-Term Memory Algorithm and MODIS Datasets BT - Vegetation Fires and Pollution in Asia," K. P. Vadrevu, T. Ohara, and C. Justice, Eds. Cham: Springer International Publishing, 2023, pp. 589–602.

[8] S. H. Rafi, Nahid-Al-Masood, S. R. Deeba, and E. Hossain, "A Short-Term Load Forecasting Method Using Integrated CNN and LSTM Network," *IEEE Access*, vol. 9, pp. 32436–32448, 2021, doi: 10.1109/ACCESS.2021.3060654.

[9] D. Johnson, A. Williams, and B. Miller, "Hospital Patient Data Analysis for Informed Health Policy Decision-Making," *Health Policy Plan.*, vol. 24, no. 2, pp. 178–191, 2019.

[10] J. Klaudel, B. Klaudel, M. Glaza, W. Trenkner, P. Derejko, and M. Szołkiewicz, "Forewarned Is Forearmed: Machine Learning Algorithms for the Prediction of Catheter-Induced Coronary and Aortic Injuries," *International Journal of Environmental Research and Public Health*, vol. 19, no. 24. 2022, doi: 10.3390/ijerph192417002.

[11] X. Chen, D. Li, and J. Yang, "Machine Learning for Early Detection and Treatment of Diseases: A Review of Hospital Patient Data," *Heal. Informatics Res.*, vol. 30, no. 1, pp. 56–68, 2018.

[12] L. Clifton, D. A. Clifton, M. A. F. Pimentel, P. J. Watkinson, and L. Tarassenko, "Predictive Monitoring of Mobile Patients by Combining Clinical Observations With Data From Wearable Sensors," *IEEE J. Biomed. Heal. Informatics*, vol. 18, no. 3, pp. 722–730, 2014, doi: 10.1109/JBHI.2013.2293059.

[13] U. Satija, B. Ramkumar, and M. Sabarimalai Manikandan, "Real-Time Signal Quality-Aware ECG Telemetry System for IoT-Based Health Care Monitoring," *IEEE Internet Things J.*, vol. 4, no. 3, pp. 815–823, Jun. 2017, doi: 10.1109/JIOT.2017.2670022.

[14] M. Casal-Guisande *et al.*, "Design and Conceptual Proposal of an Intelligent Clinical Decision Support System for the Diagnosis of Suspicious Obstructive Sleep Apnea Patients from Health Profile," *International Journal of Environmental Research and Public Health*, vol. 20, no. 4. 2023, doi: 10.3390/ijerph20043627.

[15] M. S. Paulo, M. Peyroteo, M. R. Maia, C. Pries, C. Habl, and L. V. Lapão, "Impacts of public health and social measures on COVID-19 in Europe: a review and modified Delphi technique," *Front. Public Heal.*, vol. 11, no. 1, pp. 1–15, 2023, doi: 10.3389/fpubh.2023.1226922.

[16] A. G. Stewart, W. Shepherd, R. Jarvis, and S. Ghebrehewet, "Environmental Public Health practice: designing and delivering a locally desirable service," *Public Health*, vol. 221, pp. 150–159, 2023, doi: https://doi.org/10.1016/j.puhe.2023.06.009.

[17] E. A. Kadir, S. M. Shamsuddin, T. A. Rahman, and A. Samad Ismail, "Big Data Network Architecture and Monitoring Use Wireless 5G Technology," *Int. J. Adv. Soft Compu. Appl*, 2015.

[18] E. A. Kadir, A. Siswanto, and A. Yulian, "Home Monitoring System Based on Cloud Computing Technology and Object Sensor," in *Proceedings of the Second International Conference on the Future of ASEAN (ICoFA) 2017 – Volume 2*, 2018.

[19] D. R. Y. Gan *et al.*, "Neighborhood Makes or Breaks Active Ageing? Findings from Cross-Sectional Path Analysis," *International Journal of Environmental Research and Public Health*, vol. 19, no. 6. 2022, doi: 10.3390/ijerph19063695.

[20] C. M. Bishop, *Neural networks for pattern recognition*. USA: Oxford University Press, 1995.

ICICT

ORIGINALITY REPORT

15%	4%	15%	1%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Lenni Dianna Putri, Ermi Girsang, I Nyoman Ehrich Lister, Hsiang Tsung Kung, Evizal Abdul Kadir, Sri Listia Rosa. "Public Health Implications for Effective Community Interventions Based on Hospital Patient Data Analysis Using Deep Learning Technology in Indonesia", Information, 2024 Publication	12%
2	www2.mdpi.com Internet Source	1%
3	Sri Listia Rosa, Evizal Abdul Kadir, Abdul Syukur, Hitoshi Irie, Rizky Wandri, Muhammad Fikri Evizal. "Fire Hotspots Mapping and Forecasting in Indonesia Using Deep Learning Algorithm", 2022 3rd International Conference on Electrical Engineering and Informatics (ICon EEI), 2022 Publication	1%

Exclude quotes On

Exclude matches < 1%

Exclude bibliography On