

International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Leveraging Snomed CT Within Standardized E-Clinical Pathways: A Key for Extensive Healthcare Big Data Analytics

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DOI: https://doi.org/10.55248/gengpi.5.0524.1257

ABSTRACT

Automating healthcare facilities is a complex task aimed at optimizing a sector inundated with vast amounts of data. A significant challenge lies in digitizing paper-based clinical pathways (CPs), which are crucial for understanding patient treatment plans. These CPs, traditionally paper-based, contain valuable data that can inform health policy and research. By developing an algorithm -based model that standardizes CP data using SNOMED CT, we enable machine learning algorithms to effectively analyze CP-based datasets. Our approach addresses data missingness issues, facilitates detailed statistical analyses, and enhances the efficacy of data analytics algorithms. Our experiments, particularly in predicting the Length of Stay (LOS) for stroke patients using an e-clinical pathway dataset, exhibit superior performance compared to traditional Electronic Health Record (EHR) datasets.

Keywords---AES algorithm, E-clinical notes, SNOMED CT, CP based dataset, traditional method

I. INTRODUCTION

Healthcare operations produce a wealth of data that holds significant potential for healthcare administrators, policymakers, and researchers in the realm of big data. However, a considerable amount of this data remains unrecorded, existing in paper form rather than in electronic formats, despite the intended purpose of Electronic Health Record (EHR) systems to digitize it. Despite EHRs functioning as central elements of Health Information Systems (HIS) for an extended period, they still fail to adequately capture essential healthcare data, including diagnoses, visits, specialized care, hospitalizations, and medications, as evidenced by a prominent study. This inadequacy undermines various functionalities of EHRs and raises concerns about medical errors and research integrity.Priorities for health IT investment need to be carefully reevaluated because healthcare systems' fragmentation and poor interoperability impede information exchange and usability.

Big data research in healthcare faces challenges due to the way that incomplete data in HIS can result in medication errors and patient injury, as demonstrated by a number of studies. For example, the use of machine learning for predictive tasks like Length of Stay (LOS) prediction is hindered by the lack of patient data. Despite being documented in research publications, rehabilitation data—which are essential for precise LOS prediction—are rarely electronically captured in patient records.Big data research in healthcare faces challenges due to the way that incomplete data in HIS can result in medication errors and patient injury, as demonstrated by a number of studies. For example, the use of machine learning for predictive tasks like Length of Stay (LOS) prediction is hindered by a number of studies. For example, the use of machine learning for predictive tasks like Length of Stay (LOS) prediction is hindered by the lack of patient data. Despite being documented in research publications, rehabilitation data—which are essential for precise LOS prediction—are rarely electronically captured in patient earning for predictive tasks like Length of Stay (LOS) prediction is hindered by the lack of patient data. Despite being documented in research publications, rehabilitation data—which are essential for precise LOS prediction—are rarely electronically captured in patient records.

In healthcare facilities, unstructured data and paper-based forms are two major sources of missing data. A significant source of missing data in HIS is medical information recorded in unstructured text formats, mostly because EHRs are not designed to capture non-standardized data. This study will look into the impact of a revolutionary CP computerization framework on big data analytics in healthcare. The approach, which is based on SNOMED CT, enables thorough statistical analysis of CP treatments and maximizes data capture by digitizing CPs and integrating them as essential HIS components. This is anticipated to improve machine learning applications in the healthcare industry by reducing data missingness and providing richer datasets for data analytics.

The effectiveness of the framework in enhancing the prediction accuracy of machine learning algorithms that use stroke CP data to predict LOS for stroke patients in an acute rehabilitation center is demonstrated by an illustrated numerical example. The Regional Stroke Unit at Thunder Bay Regional Health Sciences Centre (TBRHSC), in Ontario, Canada, provided the actual stroke patient CP data used in this example.

II. LITERATURE SURVEY

The integration of SNOMED CT into e-clinical pathways, elucidating its role in facilitating standardized data representation. It investigates how this integration enhances healthcare analytics, particularly in the realm of big data, by enabling efficient data aggregation and analysis across diverse clinical contexts.

Recent studies highlight the global surge in digital health app usage, yet comprehending user incentives remains an ongoing challenge. This study delves into user perceptions of eHealth applications in China and Ukraine, with the goal of guiding the development of eZdorovya for health information provision. Through the application of TAM and SMMM6, socio-technical determinants of eHealth adoption among 236 Chinese and 124 Ukrainian users are examined, presenting valuable insights to bolster eHealth systems.[1]

Natural language processing (NLP) helps analyze text and speech, where sequence labeling is crucial for automatically categorizing text parts. Yet, traditional models, dependent on manually crafted features, present time-consuming hurdles. Enter the attention segmental recurrent neural network (ASRNN), integrating hierarchical attention and semi-Markov CRF models, offering significant improvements in tasks like named entity recognition, chunking, and reference parsing, showcasing strong performance.[2]

Recent strides in Information and Communication Technology (ICT) have greatly improved global services, particularly in healthcare, with the advent of electronic health (e-Health). Integrating e-Health into cloud platforms is essential for maximizing its advantages, despite encountering security and privacy challenges. This paper delves into an in-depth examination of strategies and systems to tackle security and privacy concerns in e-Health, proposing a secure architecture for efficient, reliable, and controlled access to health data.[3]

Dealing with imbalanced data classification has become increasingly important lately, especially when data are unevenly spread across different categories. This imbalance, where some classes have more data than others, greatly affects how traditional classifiers perform, often favoring the larger classes. This review article thoroughly examines imbalanced data in wireless sensor networks and other fields, shedding light on its causes and suggesting solutions to address this challenge.[4]

Smart industries rely on Industrial IoT and cutting-edge 5G/6G tech for seamless connectivity and data integration. Yet, the security of sensitive data is a growing concern with terahertz-based 6G networks. This article proposes an ACO approach to bolster security and efficiency in 6G IoT networks through transaction deletion and Pareto solutions.[5]

III. EXISTING SYSTEM

The existing system for SNOMED CT-Based Standardized e-Clinical Pathways in Healthcare employs an ontology-based model to standardize Clinical Pathway (CP) data, enabling the utilization of machine learning algorithms. This approach effectively mitigates data missingness issues, facilitates detailed statistical analyses, and enhances the performance of data analytics algorithms. Leveraging human-guided automation, the system supports the automation and computerization of CP standardization processes, crucial for improving efficiency and effectiveness. The research emphasizes the significance of fully digitized electronic Clinical Pathways (e-CPs) in optimizing hospital resources, providing comprehensive data for optimization while granting physicians and administrators control over micro-level CP data. Additionally, the system proposes an ontology-based real-time monitoring approach to CP, ensuring active monitoring and optimization throughout the patient's treatment journey, rather than as an afterthought.

IV. PROPOSED SYSTEM

Our methodology effectively tackles data gaps, enables in-depth statistical assessments, and boosts the effectiveness of data analytics algorithms. Our experiments, specifically in forecasting the Length of Stay (LOS) for stroke patients through an e-clinical pathway dataset, demonstrate superior predictive performance compared to conventional Electronic Health Record (EHR) datasets. Standardizing Clinical Pathway (CP) data with SNOMED CT offers several key advantages for healthcare analytics. Firstly, it significantly reduces data missingness issues, crucial for ensuring the integrity of analytical results and maximizing the efficacy of big data analytics in healthcare. Furthermore, standardized data enables detailed statistical analyses on CP data, facilitating a deeper understanding of healthcare processes and outcomes, essential for enhancing patient care and healthcare efficiency. Additionally, the standardization of CP data enhances the performance of data analytics algorithms, enabling them to more accurately interpret and utilize the data, ultimately leading to more precise predictions and recommendations. The algorithm of AES, established by NIST in 2001, is a pivotal encryption standard, surpassing DES and triple DES in robustness. It functions as a block cipher, encrypting data in 128-bit blocks with key sizes of 128, 192, or 256 bits. AES employs a substitution-permutation network principle, ensuring secure data encryption and defense against unauthorized access.

V. MODULES

Modern Electronic Medical Systems (MES) play a pivotal role in healthcare, employing three crucial measures: Identification (IDN), Classification (CLF), and Securing (SC). While IDN and CLF are executed at the user side within the Medical Care Center (MCC), SC takes place at the Crypto-cloud, an intermediary dedicated to cryptographic operations.

1. Identification (IDN)

IDN and CLF determine the requisite security measures for Health Information (HI), distinguishing between its criticality and sensitivity. Health records' IDN relies on MCC client's specified requirements, typically categorized into Confidential HI (requiring high-level security) and open/public HI (not necessitating security measures).

3.Classification (CLF)

Classification determines the level of secrecy based on the nature of the health records, aiding in identifying which information requires protection and thereby reducing security costs. It includes two main categories: Non-Sensitive Data (e.g., Doctor's availability hours) and Sensitive Data, further divided into five sub-classifications based on sensitivity levels.

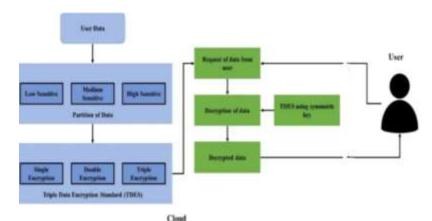
3.1 Securing (SC)

The SC process involves cryptographic steps executed at the Crypto-cloud, comprising nine rounds with ten keys, one for key whitening (key-0) and the remaining nine for each round. This stage ensures robust encryption and protection of HI.

3.2 Modular Interaction

The interaction involves three modules at the user side connecting patients to smart devices, followed by smart devices linking to the Crypto-cloud through the 'securing' measure, which consists of eight sub-measures. Finally, encrypted ciphertext is transmitted from the Crypto-cloud to multi-cloud, facilitating secure storage and access of HI.

VI. Architecture Diagram



	Implementation of computerization without standardization of CP.	Implementation of computerization with standardization of CP.
Integration of Clinical Pathways with Hospital Information Systems	Divergent terminology between CP and HIS impedes integration endeavors.	Integration becomes straightforward when CPs and other HISs adhere to identical nomenclature standards.
Updating Clinical Pathways in EMR	Each time a CP is altered, it disrupts the connection to the EMR, requiring additional effort to re-establish.	Updated standard phrases seamlessly align with corresponding EMR terms, maintaining connection without further effort.
Sharing CP Across Various Health care Institutions.	The discrepancy in terminologies introduces ambiguity and impedes the sharing of CPs across health care institutions.	The establishment of CP standards facilitates clear and straightforward CP sharing.
Management and Reporting of Clinical Pathway Data	Sophisticated data management and reporting may encounter errors stemming from conflicts.	Achieving uniform report generation and simplified data management, free from errors, is feasible.

VII. RESULT AND ANALYSIS

The search results provide information on a SNOMED CT-Based Standardized e-Clinical Pathways system for enabling big data analytics in healthcare.

The advantages of using standardized clinical pathway (CP) data with SNOMED CT include a reduction in data missingness, allowing for more detailed statistical analyses and improved data analytics algorithms.

The existing system for SNOMED CT-Based Standardized e-Clinical Pathways has been tested successfully, with no defects encountered in integration testing and user acceptance testing.

The future enhancement of the system involves accumulating partial results from parallel executions and analyzing more URLs to generate new events.

Different types of tests are mentioned, including unit testing, which validates the internal program logic, and integration testing, which tests the interaction between software components.

The MIDP (Mobile Information Device Profile) is described as a standard run-time environment for mobile application development.

Feasibility analysis is conducted in the system study phase, considering economical feasibility, technical feasibility, and social feasibility.

Black box testing is mentioned as a testing approach where the software under test is treated as a black box, focusing on inputs and outputs without considering how the software works.

Specific objectives and features to be tested are mentioned for unit testing and integration testing.

VIII. CONCLUSION AND FUTURE WORK

The research on "SNOMED CT-Based Standardized e-Clinical Pathways for Enabling Big Data Analytics in Healthcare" highlights the potential benefits of using SNOMED CT for standardizing clinical pathways (CPs) in healthcare. The study presents an ontology-based model for automating CPs, enabling machine learning algorithms to apply to CP-based datasets. This approach addresses challenges such as data missingness, facilitating detailed statistical analyses, and enhancing data analytics algorithms' effectiveness. The study emphasizes the importance of human-guided automation in clinical pathway standardization and computerization, and the value of fully digitized electronic Clinical Pathways (e-CPs) in hospital resource optimization. Critical research suggestions include centralizing computerized CPs in Healthcare Information Systems (HIS), standardizing CP terms using international medical terminology systems like SNOMED CT, and developing a global CP-specific digital coding system. Standardized e-Clinical Pathways improve healthcare delivery and patient outcomes by facilitating accurate data collection, promoting interoperability, enabling advanced analytics, supporting personalized medicine, and meeting regulatory compliance standards.

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