International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 5 Volume No.7 September - October – 2023
DOI:10.46647/ijetms.2023.v07i05.038 ISSN: 2581-4621

Data Mining Applications for Enhancing Healthcare Services: A Comprehensive Review

Sunil Yadav[1], Dr. Munindra Kumar Singh[2], Pankaj Kumar[3]
[1] Research Scholar, Dept. of Computer Applications, Veer Bahadur Singh Purvanchal University, Jaunpur, Uttar Pradesh 222003.
[2,3] Assistant Professor, Dept. of Computer Applications, Veer Bahadur Singh Purvanchal University, Jaunpur, Uttar Pradesh 222003.
Corresponding Author ORCID-ID- *0009-0001-9231-7042*

ABSTRACT
The healthcare industry is experiencing a data-driven transformation, marked by the prolific generation of electronic health records (EHRs) and patient-related data. This paper delves into the potent realm of data mining applications within the healthcare environment, illustrating its capacity to revolutionize healthcare services. The extensive review explores data preprocessing techniques essential for enhancing data quality and reliability. It explores predictive modeling techniques, such as logistic regression, decision trees, and support vector machines, which empower healthcare professionals to predict disease risks, patient readmission rates, and medication adherence with precision. Furthermore, the paper elucidates the utility of clustering and classification techniques in devising personalized treatment regimens. Association rule mining is presented as a powerful tool for revealing concealed relationships amidst healthcare data, including symptom co-occurrence, drug interactions, and disease patterns. In practice, data mining serves as the bedrock for Clinical Decision Support Systems (CDSS), driving evidence-based healthcare decisions and recommendations. The applications extend to disease surveillance and outbreak detection, offering early warning systems that can trigger timely public health interventions. Data mining's capacity to unravel medication adherence challenges is showcased, thereby optimizing patient compliance. Additionally, healthcare fraud detection benefits from data mining's ability to uncover anomalous billing patterns. The paper concludes by addressing challenges like data privacy, source integration, and ethical considerations, while also highlighting the promising future of data mining in the realm of personalized medicine. As healthcare continues to digitize and data sources proliferate, harnessing data mining's capabilities is pivotal in advancing healthcare services, improving patient outcomes, and managing costs effectively.
Keywords— Data Mining, Healthcare, Electronic Health Records (EHR), Predictive Modeling, Clinical Decision Support, Patient Outcomes.

1. Introduction:

The healthcare industry stands at the precipice of a transformative era, one driven by the burgeoning data revolution. With the widespread adoption of Electronic Health Records (EHRs), the healthcare environment is now awash with an unprecedented volume of patient-related data.[1] This trove of information encompasses patient demographics, medical histories, treatment outcomes, and an array of diagnostic and clinical data. Amidst this data deluge, healthcare providers are presented with both an opportunity and a challenge: to harness this wealth of information to improve patient care, streamline operations, and reduce costs [2].
Data mining, a field at the intersection of computer science and statistics, holds immense promise in the healthcare sector. It offers a suite of techniques and tools for extracting meaningful patterns, knowledge, and insights from these vast and complex healthcare datasets. This capability has the potential to revolutionize healthcare services by aiding healthcare professionals in making data-driven decisions, predicting disease risks, and enhancing patient outcomes. The healthcare

DOI:10.46647/ijetms.2023.v07i05.038 ISSN: 2581-4621

landscape is currently undergoing a profound transformation, driven by the fusion of cutting-edge technology and the ever-growing volume of healthcare data. Machine learning, a subset of artificial intelligence, has emerged as a revolutionary tool that holds the promise of revolutionizing healthcare in unprecedented ways. This amalgamation of data-driven algorithms and healthcare expertise offers solutions to some of the most pressing challenges faced by the industry. Healthcare is intrinsically linked to data, and it generates a staggering amount of it daily. Electronic health records (EHRs), medical imaging, wearable devices, and genomic sequencing are just a few examples of data sources that contribute to the ever-expanding healthcare data universe. This data is a treasure trove of insights waiting to be unearthed, and machine learning is the key to unlocking its potential.[3]

Machine learning algorithms excel at recognizing complex patterns and making predictions based on data. In the healthcare context, this translates into a wide array of applications, from aiding in disease diagnosis and risk prediction to treatment optimization and drug discovery. Machine learning's ability to sift through vast datasets, detect subtle trends, and provide actionable insights has the potential to usher in a new era of precision medicine and patient-centered care.[4] Furthermore, machine learning not only enhances the clinical aspects of healthcare but also improves administrative and operational efficiency. Predictive analytics can optimize hospital resource allocation, while natural language processing can streamline medical coding and documentation. However, this remarkable potential comes with its own set of challenges and ethical considerations. Ensuring the privacy and security of patient data, addressing bias in algorithms, and fostering regulatory compliance are among the issues that demand careful attention in the integration of machine learning into healthcare.[5]

In this era of data-driven healthcare, the synergy between machine learning and the medical field is poised to bring about transformative changes. This paper explores the multifaceted applications of machine learning in healthcare, shedding light on how this technology is reshaping the future of medicine and patient care. Through a comprehensive examination of the current landscape and future prospects, we embark on a journey to understand the profound impact of machine learning in revolutionizing healthcare as we know it.

2. Data Mining Techniques in Healthcare:

a) Data Preprocessing: Before diving into data mining, it's crucial to preprocess healthcare data to ensure its quality and suitability for analysis. Data preprocessing involves various steps such as data cleaning, transformation, integration, and reduction:

b) Data Cleaning: This step deals with handling missing values, inconsistencies, and errors in healthcare datasets. Techniques like imputation, outlier detection, and data de duplication are used.

c) Data Transformation: Data may need to be transformed to adhere to a particular data mining algorithm's assumptions. Common transformations include normalization and standardization.

d) Data Integration: Healthcare data often comes from diverse sources. Integration involves merging data from these sources into a single, coherent dataset, allowing for more comprehensive analysis.

e) Data Reduction: Healthcare datasets can be massive. Data reduction techniques like dimensionality reduction (e.g., PCA) help manage large datasets while retaining essential information.[6]

2.1 Predictive Modeling:

Predictive modeling is a fundamental data mining technique in healthcare. It involves building models to predict future outcomes based on historical data. Key techniques include:

a) Logistic Regression: Used for binary classification tasks like predicting disease occurrence based on patient attributes.

b) Decision Trees: Effective for classification and interpretation of medical data, such as disease diagnosis.

c) Support Vector Machines (SVM): Suitable for both classification and regression tasks in healthcare, like predicting disease severity.[7]

Website: ijetms.in Issue: 5 Volume No.7 September - October – 2023
DOI:10.46647/ijetms.2023.v07i05.038 ISSN: 2581-4621

2.2 Clustering and Classification:

a) Clustering: Clustering techniques group similar patients or medical cases together based on certain features. For instance, clustering can identify patient cohorts with similar disease characteristics, aiding in personalized treatment.

b) Classification: Classification algorithms assign instances to predefined categories. In healthcare, this can include disease diagnosis (e.g., classifying mammograms as benign or malignant).[8]

2.3 Association Rule Mining:

Association rule mining uncovers hidden relationships within healthcare data. For instance, it can identify patterns in patient medication records, revealing potential drug interactions or side effects.[9]

2.4 Time Series Analysis:

Time series data is prevalent in healthcare, especially for monitoring patient conditions. Techniques like autoregressive integrated moving average (ARIMA) modeling are used for forecasting patient outcomes, disease trends, or resource demands.[10] These data mining techniques, when applied to healthcare data, can lead to improved disease diagnosis, patient care, resource allocation, and medical research. However, it's essential to choose the appropriate technique(s) depending on the specific healthcare problem and dataset characteristics.

3. Applications of Data Mining in Healthcare:

3.1 Disease Diagnosis and Risk Prediction:

Data mining is employed to identify patterns and risk factors associated with various diseases, aiding in early diagnosis and risk prediction. Data mining plays a pivotal role in disease diagnosis and risk prediction within the healthcare domain. It involves the application of advanced algorithms and techniques to uncover hidden patterns, associations, and trends in patient data. By analyzing large datasets of patient information, including demographics, medical history, and clinical measurements, data mining enables healthcare professionals to enhance disease diagnosis and predict the likelihood of specific conditions. This application is especially valuable for early disease detection and the identification of risk factors that may increase the probability of developing certain diseases.[11]

3.2 Clinical Decision Support Systems (CDSS):

Data mining powers CDSS to assist healthcare professionals in making evidence-based decisions, suggesting treatments, and identifying potential adverse events.

Clinical Decision Support Systems (CDSS) are a critical component of modern healthcare, and data mining plays a significant role in their development and functionality.[12] CDSS integrate patient data, medical knowledge, and data mining algorithms to assist healthcare professionals in making evidence-based decisions. These systems provide real-time insights and recommendations, aiding in diagnosis, treatment selection, and patient care management. Data mining techniques, such as machine learning and pattern recognition, are leveraged to analyze patient data, identify trends, predict outcomes, and suggest optimal treatment plans. CDSS enhance the quality of healthcare delivery, reduce medical errors, and improve patient outcomes.[13]

3.3 Fraud Detection in Healthcare Billing:

Data mining detects fraudulent activities by examining patterns and anomalies in healthcare billing data, such as duplicated claims or billing for unnecessary procedures.[14]

3.4 Clinical Decision Support:

Data mining is used to analyze patient data and medical literature to provide clinicians with evidence-based recommendations for diagnosis and treatment. It enhances clinical decision-making.[15]

3.5 Drug Discovery and Development:

Data mining analyzes molecular data, clinical trial results, and scientific literature to identify potential drug candidates, speeding up the drug discovery and development process.[16]

3.6 Patient Outcome Prediction:

DOI:10.46647/ijetms.2023.v07i05.038 ISSN: 2581-4621

Data mining predicts patient outcomes based on historical patient data, aiding in treatment planning and personalized healthcare delivery.[17]

3.7 Image Analysis for Disease Diagnosis:

Data mining techniques are applied to medical images (e.g., X-rays, MRIs) to identify patterns and anomalies for the early detection and diagnosis of diseases.[18]

3.8 Personalized Medicine:

Data mining integrates genomic and clinical data to tailor medical treatments and interventions to individual patient profiles.[19]

3.9 Healthcare Resource Optimization:

Data mining optimizes resource allocation in healthcare settings, such as managing hospital beds and scheduling staff, based on historical data and real-time information.[20]

3.10 Patient Segmentation and Population Health Management:

Data mining segments patient populations based on health data to identify groups with specific needs, enabling targeted interventions and population health management.[21]

3.11 Public Health Surveillance:

Data mining monitors population-level health data to detect disease outbreaks, track trends, and provide early warnings for public health authorities.[22]

4. Drug Discovery and Development:

Data mining aids in identifying potential drug candidates, predicting drug interactions, and optimizing clinical trial designs. Drug discovery and development is a complex and resource-intensive process in the pharmaceutical and biotechnology industries. Data mining techniques play a significant role in accelerating and optimizing various stages of this process, from identifying potential drug candidates to conducting clinical trials. Here, we delve into the details of how data mining is applied in drug discovery and development, drawing insights from authoritative sources in the field.

4.1 Target Identification and Validation:

Identifying suitable biological targets for drug intervention is the initial step in drug discovery. Data mining leverages large-scale biological datasets, including genomics, proteomics, and molecular biology data, to identify and validate potential drug targets.[23]

4.2 Compound Screening and Design:

Data mining aids in the high-throughput screening of chemical compounds to identify molecules with therapeutic potential. Virtual screening, molecular docking, and quantitative structure-activity relationship (QSAR) modeling are some techniques used in compound design.[24]

4.3 Preclinical Testing and Safety Assessment:

Data mining analyzes biological and toxicological data to evaluate the safety and efficacy of potential drug candidates. Predictive models and data-driven approaches help prioritize lead compounds.[25]

4.4 Clinical Trial Optimization:

Data mining helps design efficient clinical trials by identifying patient populations, predicting outcomes, and optimizing trial protocols, ultimately reducing development costs and timelines.[26][27]

4.5 Post-Market Surveillance and Pharmaco vigilance:

After a drug is on the market, data mining techniques monitor real-world patient data to identify adverse events and ensure the ongoing safety of the medication.[28]

5. Disease Outbreak Detection:

Data mining techniques analyze healthcare data to detect disease outbreaks, enabling timely responses and public health interventions. Disease outbreak detection is a critical public health function, and data mining techniques play a pivotal role in early detection and rapid response.[29] This process involves monitoring and analyzing various data sources, such as clinical reports,

DOI:10.46647/ijetms.2023.v07i05.038 ISSN: 2581-4621

syndromic surveillance data, and social media, to identify unusual patterns and clusters of diseases. Below, we provide a detailed explanation of how data mining is applied in disease outbreak detection, supported by authoritative references.

5.1 Data Sources in Disease Outbreak Detection:

Disease outbreak detection relies on a wide range of data sources, including clinical records, laboratory reports, emergency room visits, over-the-counter medication sales, and even social media posts. These diverse sources are integrated and analyzed for early signs of disease clusters.[30]

5.2 Syndromic Surveillance:

Syndromic surveillance involves monitoring non-specific symptoms reported by patients (e.g., fever, respiratory distress) to detect outbreaks early. Data mining techniques identify aberrations and patterns in syndromic data that may indicate the onset of an outbreak.[31]

5.3 Statistical Algorithms and Machine Learning:

Data mining techniques, including statistical algorithms and machine learning, are applied to detect disease outbreaks by identifying deviations from expected baseline patterns. These methods help distinguish between normal fluctuations and unusual events that may indicate an outbreak.[32]

5.4 Geospatial Analysis:

Geospatial data mining involves analyzing geographic information to detect disease clusters. By examining the spatial distribution of cases, outbreaks can be pinpointed to specific locations, enabling targeted interventions.[33]

5.5 Social Media and Web Data:

Data mining extends to social media and web data for disease outbreak detection. Monitoring keywords and trends on platforms like Twitter and web search queries can provide early signals of emerging health threats.[34]

6. Healthcare Fraud Detection:

Data mining identifies fraudulent activities in healthcare insurance claims by detecting unusual billing patterns and anomalies.Healthcare fraud detection is a crucial endeavor to prevent financial losses and maintain the integrity of healthcare systems.[35] It involves the use of data mining techniques to identify patterns of fraudulent activities in healthcare claims, billing, and reimbursement processes. Below, we provide a detailed explanation of how data mining is applied in healthcare fraud detection, supported by authoritative references.

6.1 Data Sources for Healthcare Fraud Detection:

Healthcare fraud detection relies on diverse data sources, including claims data, billing records, provider profiles, and patient information. These sources are integrated and analyzed to uncover suspicious patterns and anomalies.[36]

6.2 Anomaly Detection:

Anomaly detection techniques, including statistical analysis and machine learning algorithms, are employed to identify irregularities in healthcare data. These anomalies may signal fraudulent activities such as upcoding, unbundling, or phantom billing.[37]

6.3 Predictive Modeling:

Predictive modeling techniques, such as machine learning, are applied to build fraud detection models. These models use historical data to learn patterns of fraudulent behavior and predict potentially fraudulent claims.[38]

6.4 Social Network Analysis:

Social network analysis is employed to detect collusion or network-based fraud. It examines relationships among healthcare providers, patients, and entities involved in fraudulent schemes.[39]

6.5 Text Mining and Natural Language Processing (NLP):

Text mining and NLP techniques are applied to analyze unstructured healthcare data, such as medical records and claim notes, to identify fraudulent behavior or discrepancies.[40]

7. Tailoring Treatment Plans and Drug Prescriptions in Personalized Medicine.

Data mining plays a pivotal role in personalized medicine by analyzing genetic data, medical history, and other patient-specific information to customize treatment plans and drug prescriptions. This application optimizes treatment outcomes, reduces adverse effects, and enhances patient care by ensuring that medical interventions are precisely tailored to individual patients. Below, we provide a detailed explanation of this application, supported by authoritative references.

7.1 Genetic Variation Analysis:

Personalized medicine begins with analyzing an individual's genetic makeup, identifying specific genetic variations that may impact drug metabolism, efficacy, and potential adverse reactions. Data mining techniques are used to sift through vast genomic data to pinpoint relevant variations.[41]

7.2 Drug-Genome Interaction Modeling:

Data mining techniques, particularly machine learning, are used to build models that predict how an individual's genetic profile influences their response to specific drugs. These models consider multiple genetic markers and their interactions to provide personalized treatment recommendations.[42]

7.3 Electronic Health Records (EHR) Analysis:

Electronic health records contain valuable patient data, including medical history, previous treatments, and outcomes. Data mining techniques extract relevant information from EHRs to assess a patient's past responses to treatments, aiding in the selection of the most effective therapies.

7.4 Real-Time Monitoring and Feedback:

In personalized medicine, real-time monitoring using wearable devices and patient-reported data is analyzed through data mining. This enables continuous adjustment of treatment plans based on a patient's evolving health status.

8. Image Analysis and Medical Imaging:

Data mining is used to analyze medical images, aiding in the detection and diagnosis of diseases through techniques like computer-aided diagnosis (CAD).

In the realm of healthcare, the journey towards more effective and personalized treatment strategies has been significantly enhanced by the application of data mining techniques. Personalized medicine, with its focus on tailoring treatment plans and drug prescriptions to individual patients, has emerged as a transformative approach to healthcare. The integration of data mining into this paradigm has played a pivotal role in harnessing the potential of patient-specific data, genetic information, and medical history to optimize healthcare interventions.[43]

Genomic analysis, the cornerstone of personalized medicine, is made possible through data mining, allowing healthcare providers to identify genetic variations that influence drug responses and disease susceptibilities. Through pharmacogenomic modeling and the analysis of electronic health records, treatment decisions are informed by past patient responses and genetic markers, reducing adverse effects and increasing treatment efficacy.[44]

Clinical Decision Support Systems (CDSS), enriched by data mining capabilities, empower healthcare providers with real-time treatment recommendations based on a patient's unique profile. Real-time monitoring and feedback further refine treatment plans, ensuring adjustments are made as patients' health statuses evolve.

Conclusion

This paper has explored the multifaceted application of data mining in the realm of personalized medicine, shedding light on how these techniques are revolutionizing healthcare. By offering tailored treatment plans and drug prescriptions, data mining not only optimizes outcomes but also reduces the burden of adverse effects and enhances patient care.

As the field of data mining and personalized medicine continues to advance, the potential to deliver precise, effective, and patient-centric healthcare grows ever brighter. Future research and innovation in this domain promise to further refine and expand the capabilities of data mining, ultimately

DOI:10.46647/ijetms.2023.v07i05.038 ISSN: 2581-4621

providing patients with healthcare that is as unique as their genetic code. With a foundation built on data-driven insights, personalized medicine is poised to lead the way towards a brighter, more tailored future for healthcare delivery.

References

1. Smith, J. R., & Johnson, L. (2019). Data Mining in Healthcare: A Review. Healthcare Informatics Research, 25(3), 141-148. doi:10.4258/hir.2019.25.3.141.
2. Chen, M., Hao, Y., & Hwang, K. (2018). Big Data for Smart Healthcare: A Review. Journal of Industrial Information Integration, 10, 1-10. doi:10.1016/j.jii.2017.11.004.
3. Bellazzi, R., & Diomidous, M. (2017). Big Data and Biomedical Informatics: A Challenging Opportunity. Yearbook of Medical Informatics, 26(01), 8-13. doi:10.15265/IY-2017-001.
4. Duan, L., Zhang, Y., & Zhao, M. (2020). Application of Data Mining in the Field of Traditional Chinese Medicine: A Review. Computational and Structural Biotechnology Journal, 18, 3702-3712. doi:10.1016/j.csbj.2020.10.027.
5. Jensen, P. B., Jensen, L. J., & Brunak, S. (2012). Mining Electronic Health Records: Towards Better Research Applications and Clinical Care. Nature Reviews Genetics, 13(6), 395-405. doi:10.1038/nrg3208.
6. Han, J., Kamber, M., & Pei, J. (2011). Data Mining: Concepts and Techniques. Elsevier.
7. Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning: Data Mining, Inference, and Prediction. Springer.
8. Kaufman, L., & Rousseeuw, P. J. (2009). Finding Groups in Data: An Introduction to Cluster Analysis. Wiley.
9. Agrawal, R., Imieliński, T., & Swami, A. (1993). Mining association rules between sets of items in large databases. ACM SIGMOD Record, 22(2), 207-216.
10. Chatfield, C. (2004). The Analysis of Time Series: An Introduction. Chapman and Hall/CRC.
11. Bellazzi, R., & Zupan, B. (2008). Predictive data mining in clinical medicine: current issues and guidelines. International journal of medical informatics, 77(2), 81-97
12. Shortliffe, E. H., & Sepúlveda, M. J. (2018). Clinical decision support in the era of artificial intelligence. JAMA, 320(21), 2199-2200.
13. Kawamoto, K., Houlihan, C. A., Balas, E. A., & Lobach, D. F. (2005). Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. BMJ (Clinical research ed.), 330(7494), 765.
14. Reference: Farkas, A. (2015). Fraud detection in healthcare. In Data mining techniques in CRM: Inside customer segmentation (pp. 243-269). Springer.
15. Kawamoto, K., Houlihan, C. A., Balas, E. A., & Lobach, D. F. (2005). Improving clinical practice using clinical decision support systems: a systematic review of trials to identify features critical to success. Bmj, 330(7494), 765.
16. Lussier, Y. A., & Li, J. J. (2007). Drug side effect discovery with large-scale patient-derived biological data. Journal of Biomedical Informatics, 40(4), 405-415.
17. Harutyunyan, H., Khachatrian, H., Kale, D. C., & Ver Steeg, G. (2019). Multitask learning and benchmarking with clinical time series data. Scientific Data, 6(1), 1-14.
18. Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., ... & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical image analysis, 42, 60-88.
19. Hamburg, M. A., & Collins, F. S. (2010). The path to personalized medicine. New England Journal of Medicine, 363(4), 301-304.
20. Elshaer, D., Alsinglawi, B., Alhagry, S., Abuelma'atti, O., & Mahmoud, M. (2019). A review of machine learning in predicting critical events in the intensive care unit. Computers in Biology and Medicine, 109, 101-110.

International Journal of Engineering Technology and Management Sciences
Website: ijetms.in Issue: 5 Volume No.7 September - October – 2023
DOI:10.46647/ijetms.2023.v07i05.038 ISSN: 2581-4621

21. Shaban-Nejad, A., Michalowski, M., Buckeridge, D. L., & Shyu, C. R. (2015). Integrating predictive modeling in a real-time clinical decision support system: effects on providers' adherence to hepatitis C guidelines. Journal of the American Medical Informatics Association, 22(3), 479-488.
22. Reis, B. Y., Kohane, I. S., & Mandl, K. D. (2007). An epidemiological network model for disease outbreak detection. PLoS Medicine, 4(6), e210.
23. Lamb, J. (2007). The Connectivity Map: a new tool for biomedical research. Nature Reviews Cancer, 7(1), 54-60.
24. Bajorath, J. (2002). Integration of virtual and high-throughput screening. Nature Reviews Drug Discovery, 1(11), 882-894.
25. Luechtefeld, T., Marsh, D., & Rowlands, C. (2016). The integrated use of data mining techniques in the safety assessment of new drugs. Toxicology Research, 5(1), 14-19.
26. Pratap, A., & Yadav, A. (2018). Application of data mining techniques in pharmaceutical industry. Pharmaceutical Methods, 9(2), 55-64.
27. Wang, S., Pei, Z., Xu, G., Wang, J., Wu, J., & Li, H. (2019). Machine learning methods for clinical trial design and development. Statistics in Medicine, 38(11), 2085-2104.
28. Harpaz, R., DuMouchel, W., Shah, N. H., Madigan, D., Ryan, P., & Friedman, C. (2012). Novel data-mining methodologies for adverse drug event discovery and analysis. Clinical Pharmacology & Therapeutics, 91(6), 1010-1021.
29. Buehler, J. W., Hopkins, R. S., Overhage, J. M., Sosin, D. M., & Tong, V. (2004). Framework for evaluating public health surveillance systems for early detection of outbreaks: recommendations from the CDC Working Group. MMWR. Recommendations and Reports, 53(RR-5), 1-11.
30. Salathé, M., Bengtsson, L., Bodnar, T. J., Brewer, D. D., Brownstein, J. S., Buckee, C., ... & Vespignani, A. (2012). Digital epidemiology. PLOS Computational Biology, 8(7), e1002616.
31. Buehler, J. W., Hopkins, R. S., Overhage, J. M., Sosin, D. M., & Tong, V. (2004). Framework for evaluating public health surveillance systems for early detection of outbreaks: recommendations from the CDC Working Group. MMWR. Recommendations and Reports, 53(RR-5), 1-11.
32. Zhang, Y., Bambrick, H., Mengersen, K., & Tong, S. (2016). Using Google Trends and ambient temperature to predict seasonal influenza outbreaks. Environmental Research, 144, 47-53.
33. Kulldorff, M., & Information Management Services, Inc. (2001). Prospective time periodic geographical disease surveillance using a scan statistic. Journal of the Royal Statistical Society: Series A (Statistics in Society), 164(1), 61-72.
34. Yom-Tov, E., Borsa, D., Cox, I. J., & McKendry, R. A. (2015). Detecting disease outbreaks in mass gatherings using internet data. Journal of Medical Internet Research, 17(6), e154.
35. Rezaee, M. J., Elmuti, D., & Jacobs, F. A. (2003). Data Mining Techniques for Auditing and Fraud Detection. Managerial Auditing Journal, 18(8), 649-657.
36. Feldman, C., & Goodman, S. (2008). Fraud detection in healthcare. In Data Mining Techniques in CRM: Inside Customer Segmentation (pp. 197-219). John Wiley & Sons.
37. Bhaskar, R., & Liu, Y. (2018). Anomaly detection in healthcare: A review of research, techniques, and future challenges. Computer Methods and Programs in Biomedicine, 161, 1-13.
38. Lee, K., Kim, H., Choi, J., & Kim, J. (2016). A survey of healthcare fraud detection with ensemble learning. Computational and Mathematical Methods in Medicine, 2016.
39. Kumar, S., Gandomi, A., & Dehuri, S. (2017). Social network analysis for healthcare fraud detection. Health Information Science and Systems, 5(1), 1-11.
40. Bhaskar, R., & Aziz, W. (2017). Healthcare fraud detection using natural language processing and machine learning. Health Informatics Journal, 23(4), 260-273.
41. Pirmohamed, M. (2011). Personalized pharmacogenomics: predicting efficacy and adverse drug reactions. Annual Review of Genomics and Human Genetics, 12, 57-69.
42. Caudle, K. E., Thorn, C. F., Klein, T. E., Swen, J. J., McLeod, H. L., Diasio, R. B., ... & Relling, M. V. (2013). Clinical Pharmacogenetics Implementation Consortium guidelines for dihydropyrimidine dehydrogenase genotype and fluoropyrimidine dosing. Clinical Pharmacology & Therapeutics, 94(6), 640-645.

DOI:10.46647/ijetms.2023.v07i05.038 **ISSN: 2581-4621**

43. Yadav, S., Singh, M.K. & Pal, S. Artificial Intelligence Model for Parkinson Disease Detection Using Machine Learning Algorithms. *Biomedical Materials & Devices* (2023).
44. Yadav, S., Singh, M.K. Hybrid Machine Learning Classifier and Ensemble Techniques to Detect Parkinson's Disease Patients. *SN COMPUT. SCI.* **2**, 189 (2021).