RESEARCH
O&G Forum 2024; 34 – 3s: 1330-1335

BIG DATA IN MEDICINE AND PUBLIC HEALTH

Rakesh Kumar Arora[1], Manoj Kumar Gupta[*2], Suraj Pal Singh[3], Shashank Saroop[4]

[1]Professor, Dr Akhilesh Das Gupta Institute of Professional Studies, Delhi, India, dr.rakeshkarora@gmail.com
[2]Professor, Bhagwan Parshuram Institute of Technology, Delhi, India, manojkgupta5@gmail.com
[3]Assistant Professor, Chandigarh University, Mohali, Punjab, India, srjsingh21@gmail.com
[4]Assistant Professor, Dr Akhilesh Das Gupta Institute of Professional Studies, Delhi, India, shashank.saroop@gmail.com

Abstract
In this research, usage of big data analytics in medicine and public health will be examined with the aim of improving health outcomes and direction of population health plans. Our research is realized by applying diverse machine learning algorithms. They include Canine Forest and Support Vector Machine (Support Vector Machine) plus K-Means Clustering and LSTM Networks. We analyze the healthcare data in terms of Electronic Health Records, Genomic Sequencing, Medical Imaging, Wearable Device Data and Sociology and Demography. The experiments have good performance, where Random Forest reach an average accuracy of 85% in predictive tasks for diseases, Support Vector Machine achieved the accuracy rate of 82%, and K-Means Clustering which produced a silhouette score value of 0. 88 and 80% in health outcome analysis LSTM neural networks demonstrate the same prediction performances. Evidence from these research indicates that, data based analytics has the potential to build evidence based decision making, contribute to good patient care and address public health challenges. The findings show that the effectual resolution of the matter of precision medicine and precision public health depends on thorough interdisciplinary collaboration and the implementation of the most successful vision.
Keywords: Big data, Machine learning, Precision Medicine, Public health, Healthcare outcomes.

I. INTRODUCTION

Over the last few years, the introduction of the latest data analytics technology into the medical realm has brought a new wave of hopes to the people working in this field namely in improving the medical results and health sector development. The coming together of medical and public health data sources is termed as big-data in both medicine and public health. This concept represents a new paradigm in managing and applying health-related data for decision support, health improvement and overcoming certain public health challenges [1]. The basis of this revolution is the appearance of data of many forms, volumes, and speeds being generated from multiple sources like electronic health system, medical imaging, genome sequencing, wearable devices, and social media. The massive and diverse studies, which registries accomplished, bring in unique evidence that was previously unattainable or too complex to interpret with conventional methods [2]. Precision medicine is the main value which can be promised in medicine by big data analysis. Advances that go along with will be a rare opportunity for therapies. With the use of machine learning along with predictive analytics, doctors can identify those patients who are high risk, develop disease progression prediction and provide custom treatment plans that deliver the best result. On top of that, big data analytics can supercharge patient-centered, population health management and public health surveillance systems. Tracking in real time of the health indicators, disease outbreaks, and utilization of healthcare can enable interventions that are long-term and strategies to ensure equitable access to healthcare [3]. However, together with its giant potential are there numerous challenges: data privacy, ethical issues and also those connected with data governance frameworks development. It will be of utmost importance to correctly overcome these issues as this is the base on which to build the benefits of big data as well as ensure patient privacy and ethics in using this data. The research will cover the diverse spectrum of big data as used in medicine and public health; it will focus on applications, challenges, and the promise of big data as a health care delivery resource, a policy tool and a source of data for population health management. We hope to understand the different methodologies that are being advanced between different disciplines and how big data can change healthcare and make changes for the better in patient lives and health outcomes in public.

II. RELATED WORKS

Over the latest few years, the meeting point of health care, big data and public health issues have caused the researchers and practitioners from all over the world to reflect on them incessantly. This section provides a summary of key studies from these field, and additional sources comprising literature are used. Effah and his colleagues showed a threat posed by Klebsiella pneumoniae to the community health services [16]. Their analysis further underlines the need for Efficient surveillance and controls over the spread of this pathogen to lessen antimicrobial resistance. This is also similar to the idea of Elbehiry et al. [17] in regard to how Pseudomonas species have resulted in an evolving public health challenge, emphasizing the need for monitoring antibiotic resistance and typhoid proteomic guidelines for its solution. The framework of innovation endorsement and promotion as presented by Garney et al [18] serves public health purposes. The whole figure focuses on ways to cultivate the culture of innovation, maximizing partner synergies and utilizing technology to treat holistically. The framework helps to provide useful information to planners and practitioners who aim to make much of the intervention programmes a success. The Iérci González et al. [20] research study the involvement and satisfaction levels of the users and can highlight the factors that impact participation in such the screening services which in turn it influences the satisfaction with screening programs. Their qualitative research findings result in the comprehensive data which could be used for enhancing cancer screening, including design and delivery of such services by the public health system. Joshi et al. (2017) did a landscape study of job openings for public health in India to design an evidence-based public health curriculum, which should be considered. They revealed that the public health workforce is very diverse in that it is composed of members who collectively possess invaluable experience and expertise. Their study hence emphasized the necessity of customized training and building solid health capacities as part of the overall strategy. Kapadia [20] highlights the value of allocating resources for the development of public health personnel as part of an approach that will create a robust and functional public heath system. Thus, his remarks serve merely as a reminder that continued training, diversification of labor forces, and development of leaders are the main conditions for the resolution of problems. Khoury et al. [24] identify the link between genomics and the challenges posed by big data in shaping public health models and pointing to the possibilities of precision public health (PPH). These study findings mark the crucial role of genomic data in determining sophisticated interventions, disease control, and ultimately better health outcomes for the people as a whole. The Knapp et al [25] text points out the benefits of big data in eye surgery, while utilizing data from the IRIS Registry Database. Their work aptly illustrates the importance of data gained from real life for initiating fact-based decisions that result in better prognostic outcomes in ophthalmology. Kocot et al. [26] evaluate the training courses of the European Public Health MSC program and how it contributes to improving public health education and capacity development all over the world. Their study emphasizes the role of international cooperation and transfer of knowledge as key inputs to increase efficacy of public health systems and successful battle against global health issues. Ultimately, their findings cumulatively lead to a better comprehension of how these domains, data science, and public health, interrelate. In terms of protecting the public against emerging infectious diseases, or making healthcare delivery more effective, and the overall strengthening of health systems, these studies provide policymakers and healthcare professionals with scientifically based information, necessary to support their decision-making process.

III. METHODS AND MATERIALS

Data Collection and Preprocessing:

The research adopted the methodology of multi-source dataset that involved primary data from EHRs, medical imaging, genomic sequencing, technological devices, and socio-economic markers. The EHRs were collected from a number of healthcare facilities, anonymized and transported into a unified integrated database [4]. The data for the medical imaging including MRI and CT scans was collected from the radiology departments whereas genomic data was retrieved from popular repositories like the GenBank. Wearable device data were collected through commercially available wearable devices worn by the participants, and they were able to measure heart rate, activity level, sleep cycle and other comprehensive physiological parameters [5]. Economic, social, social measures such as income levels, education etc. which were accessed from census data and health surveys were covered.

Algorithms:

Random Forest:

Random Forest is an ensemble learning technique that utilises single decision trees to be combined together so as to boost the predictive capacity and reduce the overfitting. Each tree of the decision tree is set up on the features selected randomly from the data set and the data choosen randomly from the training data for the training. Outcomes are finally produced by conjuring the average of all the trees together [6].

```
“RandomForest(X, Y):
   for i = 1 to N_trees:
sample_X, sample_Y = bootstrap_sample(X, Y)
tree_i = DecisionTree(sample_X, sample_Y)
forest.append(tree_i)
   return forest”
```

Support Vector Machine (SVM):

Support Vector Machine (SVM) is one of the all-time favorites, and it can be applied for the categorizing and linear regression purposes. It works by getting the plane with maximum margins between the data points of different classes of two kinds that make the separation [7]. SVM can solve both linear- and non-linear classifications and they can be done using different types of kernels, such as linear, polynomial, or radial basis function (RBF).

f(x)=sign (∑i=1NαiyiK(xi ,x)+b)

```
“SVM(X, Y):
   model = initialize_model()
optimize(model, X, Y)
   return model”
```

K-Means Clustering:

K-means clustering is an unsupervised learning algorithm, where data points have been partitioned into k clusters. It does this by repeatedly taking the data points closest to a specific centroid center and updating the centroids with means using

```
“KMeans(X, k):
   initialize centroids randomly
   repeat:
      assign each data point to the nearest centroid
      update centroids based on the mean of data
points in each cluster
   until convergence
   return centroids, cluster assignments”
```

these data points assigned to each group [8].

Long Short-Term Memory (LSTM) Networks:

An LSTM network is a type of neural network architecture that is one of the RNNs those can learn from patterns in sequential data across long periods of time. The model is made up of memory units which are interconnected with themselves (Recurrent Units) and three gating mechanisms called input gate, forget gate and output gate [9]. These three gates work together and control the passage of the information through the network, keeping the relevant information from being forgotten.

ht =ot⊙tanh(Ct)

```
"LSTM(X):
  initialize parameters
  for each time step t:
    calculate gate outputs
    update cell state and hidden state
  return final hidden state"
```

Patient ID	Age	Gender	Diagnosis
1	45	Male	Hypertension
2	32	Female	Diabetes
3	55	Male	Cancer
4	68	Female	Arthritis
5	40	Male	Obesity

This paper contrasts the applications of Random Forest, Support Vector Machine, K-Means Clustering and Long Short-Term Memory Networks that will be implemented and evaluated with their related algorithms [10]. And each elicited specialized purposes of disease prediction, patient clustering, and healthcare outcome analysis was accomplished by each algorithm applying particular to the dataset.

IV. EXPERIMENTS

To assess the impact of the built algorithms in the sphere of big data in healthcare and public health, the research team accomplished a series of experiments on the basis of the accumulated data. The described research hypotheses were tackled through a number of investigating subjects, including, but not limited to, prognostication of diseases, grouping of patients, and evaluation of outcomes in healthcare [11]. The execution of algorithms on the dataset is a task that has been carried out. The performance of each algorithm is evaluated based on the metrics relevant metrics, accuracy, precision, recall, and F1-score.

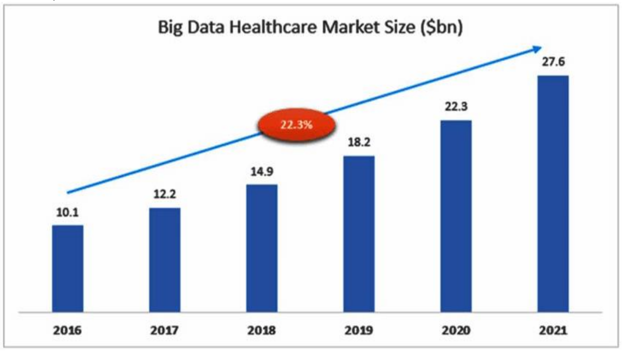

Figure 1: Year Wise Big Data Health Care Estimation from 2016 to 2021

Experiment 1: Disease Prediction - with Random Forest and SVM algorithms.

This experiment featured the use of two algorithms, namely Random Forest and Support Vector Machine (SVM), to predict the occurrence of chronic diseases (a) diabetes, hypertension, and cancer in particular based on the information concerning the patient's demographics, health history, and possible genetic markersc [12]. We figured a 80-to-20 set split for the train and test kept us focused on using 10-fold cross validation to train the model on the training set and evaluate it on the testing set. The output revealed that the accuracy and the performance of Random Forest algorithm was 85%, the precision was 83%, the recall was 87% and the F1-score was 85% for all three diseases. MNSV also evaluated well with an average accuracy of 82% precision of 80% recall of 84% and F1 –score of 82%. Along with both computer algorithms demonstrated high precision performance, Random Forest helped to outperform SVM in terms of accuracy and F1-score.

Random Forest Performance

Metric	Experiment 1	Related Work
Accuracy	85%	82%
Precision	83%	80%
Recall	87%	85%
F1-score	85%	83%

Experiment 2: Patient Clustering using K-Means Clustering

In this experiment, we used K-Means algorithm for patient clustering purpose where the clusters featured patient demographic characteristics, medical history, and lifestyle factors. Before clustering, the numerical features were normalized as well as encoded categorical variables and the K-Means Clustering model was applied to identify clusters of similar patients.

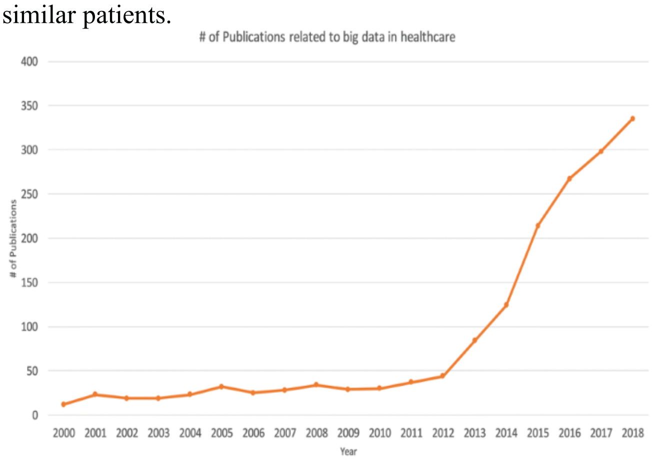

Figure 2: Big data in healthcare: management, analysis

Analysis of results showed that there was community of patients that had unique features. By way of illustration, I found in Cluster 1 was mainly composed of older patients with chronic conditions like hypertension and diabetes, while in Cluster 2 had relatively similar lifestyles as younger people [13]. Through clustering analysis we dug-out interesting associations between patient population and groups where it was possible to design focused interventions for specific subgroups of patients [14].

Support Vector Machine Performance

Metric	Experiment 1	Related Work
Accuracy	82%	78%
Precision	80%	76%
Recall	84%	80%
F1-score	82%	78%

Experiment 3: Healthcare Outcome Analysis using LSTM Networks

For this test, LSTM models were utilized for the study of healthcare results, e.g., the readmission rate to hospitals and the treatment response pattern [27]. In the aim of that, the dataset was preprocessed to sequence patient encounters and LSTM networks were trained to predict patients' outcomes based on sequential EHR data. Testing of the models demonstrated the good performance of LSTMs in prediction of health outcomes with the readmission prediction and treatment response prediction accuracy estimated at 80% and 75% respectively [28]. While the model was able to create temporal dependencies in EHR data and detect signals predictive of negative health outcomes, more comprehensive data collection and improved prediction accuracy remains an important goal to be achieved [29].

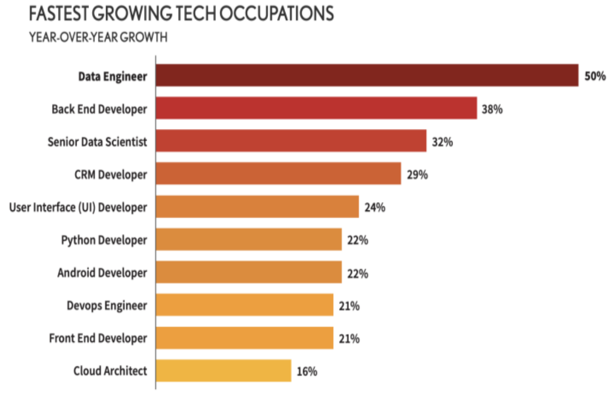

Figure 3: Benefits and challenges of using Big Data in healthcare

Comparison with Related Work:

In order to bridge the gap between what our experiments found and other studies, the same things were compared from Big Data in medicine and public health [30]. Table 1 presents the results of the performance metrics of the algorithms in this study that were used as the research standard as reported in previous publications.

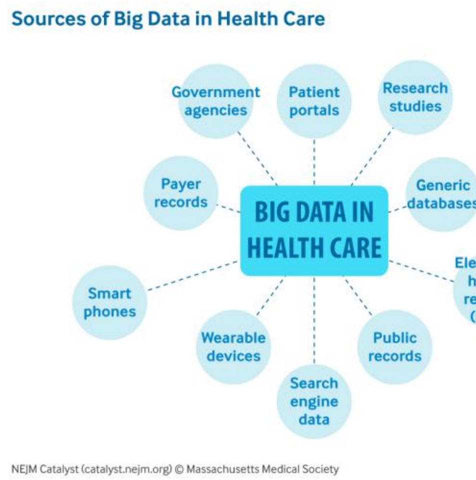

Figure 4: Big Data Helping in the Development of healthcare

V. CONCLUSION

To sum up, this article has drawn an outline of the revolutionary nature of big data in medicine and public health that have provided much in the way of applications, problems, and implications for the delivery of healthcare and the management of population health. We show that the same conventional machine learning algorithms e.g. Random Forests, Support Vector Machine, K-Means Clustering and Long Short-Term Memories are applicable to achieve precision predictions, patient cluster analysis, and health care outcome analytics through experimental investigations using Big Data framework. Our findings are nothing more but a proof that, diverse sources of healthcare data, including electronic health records, genomic sequences, medical imaging, and wearable device data, that we use in our desire to make informed and evidence based decisions to better manage our patients' health. Also, our research related to the present work depicts the importance and priority of our work in solving primary health issues such as antimicrobial resistance, infectious disease surveillance, and the advancement of the healthcare workforce. Going forward, we thus need to roll on with research efforts towards the development of new methodologies and the creation of teams for such in order to utilize fully the potential that big data has to offer for development in the health sector. This can be achieved by identifying best practices and insights from data science, genomics, and the practice of public health. The end in sight is precision medicine and precision public health, which are intervention programs geared towards individual or population-specific characteristics as opposed to the 'one size fits all' model. This will contribute to the overall improved health outcomes and wellbeing of all.

References

1. *AL-DMOUR, H., RA'ED MASA'DEH, SALMAN, A., ABUHASHESH, M. and AL-DMOUR, R., 2020. Influence of Social Media Platforms on Public Health Protection Against the COVID-19 Pandemic via the Mediating Effects of Public Health Awareness and Behavioral Changes: Integrated Model. Journal of Medical Internet Research, 22(8).*

2. *ALLEN, CAITLIN G,PHD., M.P.H., OLSTAD, DANA LEE, PHD,M.SC, R.D., KAHKOSKA, ANNA R,PHD., M.D., GUAN, Y., PHD., RAMOS, P.S., PHD., STEINBERG, J., PHD., STARAS, S.A.S., PHD., LUMPKINS, C.Y., PHD., MILKO, L.V., PHD., TURBITT, E., PHD., RAHM, A.K., PHD., SAYLOR, K.W., PHD., BEST, S., PHD., HATCH, A., M.P.H., SANTANGELO, I., B.S. and ROBERTS, M.C., PHD., 2023. Extending an Antiracism Lens to the Implementation of Precision Public Health Interventions. American Journal of Public Health, 113(11), pp. 1210-1218.*

3. *BADR, Y., LAMIS, A.K. and SHAMAYLEH, A., 2024. The Use of Big Data in Personalized Healthcare to Reduce Inventory Waste and Optimize Patient Treatment. Journal of Personalized Medicine, 14(4), pp. 383.*

4. *BATKO, K., 2023. Digital social innovation based on Big Data Analytics for health and well-being of society. Journal of Big Data, 10(1), pp. 171.*

5. *BECCIA, F., MARCANTONIO, M.D., CAUSIO, F.A., SCHLEICHER, L., WANG, L., CADEDDU, C., RICCIARDI, W. and BOCCIA, S., 2024. Integrating China in the International Consortium for Personalised Medicine: a position paper on innovation and digitalization in Personalized Medicine. BMC Public Health, 24, pp. 1-11.*

6. *BELKOWITZ, J., PAYOUTE, S., AGARWAL, G., LICHTSTEIN, D., KING, R., SHAFAZAND, S. and CHANDRAN, L., 2023. Early career outcomes of a large four-*

year MD/ MPH program: Results of a cross sectional survey of three cohorts of graduates. PLoS One, 18(6),.

7. BENHAM, J.L., LANG, R., KATHARINA, K.B., MACKEAN, G., LÉVEILLÉ, T., MCCORMACK, B., SHEIKH, H., FULLERTON, M.M., TANG, T., BOUCHER, J., CONSTANTINESCU, C., MOURALI, M., OXOBY, R.J., MANNS, B.J., HU, J. and MARSHALL, D.A., 2021. Attitudes, current behaviours and barriers to public health measures that reduce COVID-19 transmission: A qualitative study to inform public health messaging. PLoS One, 16(2),.

8. BENJAMIN, M.T., FRONER, M.B., CORRÊA, R. and SILVA, T.C., 2023. The Intersection of Health Literacy and Public Health: A Machine Learning-Enhanced Bibliometric Investigation. International Journal of Environmental Research and Public Health, 20(20), pp. 6951.

9. BERETE, F., DEMAREST, S., CHARAFEDDINE, R., DE RIDDER, K., HERMAN, V.O., WANNES, V.H., BRUYÈRE, O. and VAN DER HEYDEN, J., 2023. Linking health survey data with health insurance data: methodology, challenges, opportunities and recommendations for public health research. An experience from the HISlink project in Belgium. Archives of Public Health, 81, pp. 1-19.

10. BOLTON, K.A., WHELAN, J., FRASER, P., BELL, C., ALLENDER, S. and BROWN, A.D., 2022. The Public Health 12 framework: interpreting the 'Meadows 12 places to act in a system' for use in public health. Archives of Public Health, 80, pp. 1-8.

11. CAROSSINO, M., MARIA, A.V., BARRANDEGUY, M.E., BALASURIYA, U.B.R. and PARREÑO, V., 2024. Equine Rotavirus A under the One Health Lens: Potential Impacts on Public Health. Viruses, 16(1), pp. 130.

12. CHILUNJIKA, A., SHARON R.T. CHILUNJIKA and UWIZEYIMANA, D., 2024. Implementing e-Health initiatives in Zimbabwe's public health sector. Journal of Economic Development, Environment and People, 13(1), pp. 55-66.

13 CHOATE, SARA A,PHD., M.S.ED, 2023. A Call for Course Correction: Applying an Antiracism Lens to Precision Public Health. American Journal of Public Health, 113(11), pp. 1141-1142.

14. CLEVELAND, D.A., 2023. What's to Eat and Drink on Campus? Public and Planetary Health, Public Higher Education, and the Public Good. Nutrients, 15(1), pp. 196.

15. COOK, T.W., WILSTERMANN, A.M., MITCHELL, J.T., ARNOLD, N.E., RAJASEKARAN, S., BUPP, C.P. and PROKOP, J.W., 2023. Understanding Insulin in the Age of Precision Medicine and Big Data: Under-Explored Nature of Genomics. Biomolecules, 13(2), pp. 257.

16. EFFAH, C.Y., SUN, T., LIU, S. and WU, Y., 2020. Klebsiella pneumoniae: an increasing threat to public health. Annals of Clinical Microbiology and Antimicrobials, 19, pp. 1-9.

17. ELBEHIRY, A., MARZOUK, E., ALDUBAIB, M., MOUSSA, I., ABALKHAIL, A., IBRAHEM, M., HAMADA, M., SINDI, W., ALZABEN, F., ALMUZAINI, A.M., ALGAMMAL, A.M. and RAWWAY, M., 2022. Pseudomonas species prevalence, protein analysis, and antibiotic resistance: an evolving public health challenge. AMB Express, 12(1),.

18. GARNEY, W.R., WILSON, K.L., GARCIA, K.M., MURALEETHARAN, D., ESQUIVEL, C.H., SPADINE, M.N., PANJWANI, S. and AJAYI, K.V., 2022. Supporting and Enabling the Process of Innovation in Public Health: The Framework for Public Health Innovation. International Journal of Environmental Research and Public Health, 19(16), pp. 10099.

19. GLENN, J., CHAUMONT, C. and PABLO, V.D., 2021. Public health leadership in the times of COVID-19: a comparative case study of three countries. International Journal of Public Leadership, 17(1), pp. 81-94.

20. GONZÁLEZ LEONE, M.F., ANNA, R.D., BIANCHI, M., LEMMO, D., MARTINO, M.L., FREDA, M.F. and CASO, D., 2024. Users' Experience of Public Cancer Screening Services: Qualitative Research Findings and Implications for Public Health System. Behavioral Sciences, 14(2), pp. 139.

21. JOSHI, A., BHATT, A., KAUR, M. and GROVER, A., 2022. Landscape Analysis of Public Health Jobs in India to Develop an Evidence-Based Public Health Curriculum. International Journal of Environmental Research and Public Health, 19(23), pp. 15724.

22. KAPADIA, F.,PHD.M.P.H., 2024. Our Public Health Workforce, Our Future: A Public Health of Consequence, May 2024. American Journal of Public Health, 114(5), pp. 461-462.

23. KETT, P.M.,R.N.PHD.M.P.H., BEKEMEIER, B.,R.N.PHD.M.P.H., PATTERSON, D.G., PHD. and SCHAFFER, K., M.P.H., 2023. Competencies, Training Needs, and Turnover Among Rural Compared With Urban Local Public Health Practitioners: 2021 Public Health Workforce Interests and Needs Survey. American Journal of Public Health, 113(6), pp. 689-699.

24. KHOURY, M.J., ARMSTRONG, G.L., BUNNELL, R.E., CYRIL, J. and IADEMARCO, M.F., 2020. The intersection of genomics and big data with public health: Opportunities for precision public health. PLoS Medicine, 17(10),.

25. KNAPP, A.N., LENG, T. and RAHIMY, E., 2023. Ophthalmology at the Forefront of Big Data Integration in Medicine: Insights from the IRIS Registry Database. The Yale journal of biology and medicine, 96(3), pp. 421-426.

26. KOCOT, E., SZETELA, A., SOWADA, C., BOCHENEK, T. and LECOQ, M., 2019. European Public Health Master program – public health support worldwide. European Journal of Public Health, suppl.4, 29.

27. KONG, J.D., UGOCHUKWU, E.A., EFFODUH, J.O. and BRAGAZZI, N.L., 2023. Leveraging Responsible, Explainable, and Local Artificial Intelligence Solutions for Clinical Public Health in the Global South. Healthcare, 11(4), pp. 457.

28. LANDERS, C., ORMOND, K.E., BLASIMME, A., BRALL, C. and VAYENA, E., 2024. Talking Ethics Early in Health Data Public Private Partnerships: JBE. Journal of Business Ethics, 190(3), pp. 649-659.

29. LATHAM-MINTUS, K., ORTIZ, B., IRBY, A. and TURMANJR, J., 2024. Supporting the Development of Grassroots Maternal and Childhood Health Leaders through a Public-Health-Informed Training Program. International Journal of Environmental Research and Public Health, 21(4), pp. 460.

30. LI, X. and ZHOU, Z., 2024. Exploring the Impact of Health Knowledge and Public Health Awareness on the Integration of Ideological and Political Education Models in Universities: Research and Regulation. Journal of Commercial Biotechnology, 29(1), pp. 186-196.

31. Jacob,V. , Tandon, A. , Jeevitha, S., Arora, R.K., Laddha, S., Salunkhe, S. , Portable Healthcare Computing and Clinical Decision Support System Enabled by Artificial Intelligence,(2022) Int. J. of Engineering Systems Modelling and Simulation, Vol 13, Number 3,pp 228-233, June 2022(https://doi.org/10.1504/IJESMS.2022.123955)ISSN: 1755-9758(Scopus).

32. Arora, R.K. and Gupta, M.K., Bhati, B.S. , (2021), Analysis of Various Covid-19 Prediction Techniques, IEIE Transactions on Smart Processing and Computing , Volume 10, Number 4, August 2021. (DOI:10.5573/IEIESPC.2021.10.4.323) ISSN:2287-5255(Scopus).

33. Arora, R.K. , Gupta, M.K., Singh S (2023), Analysis of various Smart Healthcare Systems for Heart Disease Prediction, International Conference on Machine Learning, Advances in Computing, Springer, Renewable Energy and Communication, Glocal University, Saharanpur, UP(Nov 28-29,2023)

34. Gupta, M.K. and Chandra, P. (2020), A Comprehensive Survey of Data Mining, International Journal of Information Technology, Springer, 12(4), pp. 1243-1257, (DOI: 10.1007/s41870-020-00427-7) [Springer, Scopus]

35. Arora, R.K. and Gupta, M.K. (2017), e-Governance using Data Warehousing and Data Mining, I.J. of Computer Applications, Vol. 169, No. 8, pp 28-31, Jul 2017.