Migration Letters

Volume: 20, No: S12 (2023), pp. 1058-1072

ISSN: 1741-8984 (Print) ISSN: 1741-8992 (Online)

www.migrationletters.com

Optimising Urban Public Health: Network-Driven Resource Allocation For Targeted Disease Control And Outbreak Prevention

Bhanurangarao M [1], Dr. Mahaveerakannan R [2]

Abstract:
In densely populated urban areas, the swift propagation of infectious diseases presents formidable challenges in outbreak management and resource allocation. Traditional contact-tracing methods often falter amidst the intricate web of social connections within cities, resulting in delayed responses that exacerbate needless suffering, loss of life, and economic strain. This study proposes an innovative solution: resource allocation for network-driven disease control and outbreak prevention via targeted networks. By harnessing network analysis, this approach streamlines epidemic containment by directing resources precisely where they are most needed, thereby minimizing waste and optimizing resource utilization. Additionally, predictive modelling empowers pre-emptive measures to fortify resilience against future outbreaks. In essence, this research advocates for a proactive paradigm shift in urban public health, leveraging advanced analytics and strategic resource allocation to effectively combat infectious diseases while bolstering community preparedness.

Keywords: *Urban public health, Infectious disease control, Outbreak prevention, Network analysis, Social network analysis, Resource allocation, Predictive modelling.*

Introduction: Amidst the bustling opportunities and innovations found in cities, there is a heightened susceptibility to infectious diseases due to their dense population concentrations. Within these intricate urban landscapes, viruses and other pathogens thrive, exploiting the complex interconnections among individuals. Traditional contact tracing systems often falter in keeping pace with this dynamic choreography, resulting in delays in outbreak containment and inefficient resource allocation. Consequently, communities bear the burden of tragic economic losses, needless suffering, and loss of life.

This paper seeks to address this pressing challenge by proposing a transformative strategy: Enhancing Public Health[1] in Urban Areas through Network-Driven Resource Allocation for Disease Control and Outbreak Prevention. Our aim is to reshape the narrative surrounding urban epidemics by harnessing cutting-edge data science methodologies and social network research. We aim to eliminate the need for reactive responses by accurately predicting, containing, and averting epidemics in our envisioned world.

Central to this endeavor is the exploration of the unseen structures within urban social networks. By meticulously mapping and analyzing these intricate webs of connections, we can uncover hidden pathways through which disease transmission proliferates. Armed with this profound understanding, we advocate for a proactive and targeted approach. This approach redirects testing kits, medical personnel, and critical interventions to areas of highest need and potential transmission amplification, steering away from dispersed strategies that risk resource waste.

Research Scholar[1], Associate Professor[2]
Department of Computer Science and Engineering [1,2]
Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India[1,2]

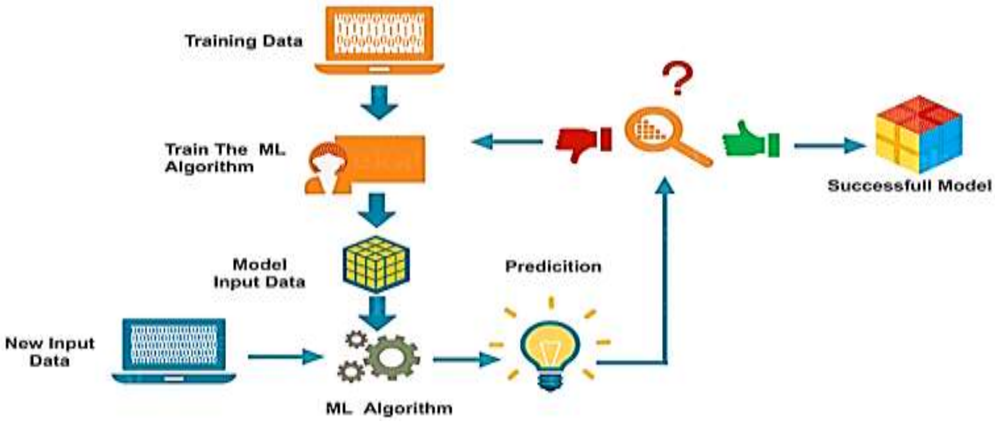
In essence, our endeavor aims to revolutionize urban public health by leveraging advanced analytics and targeted resource allocation to effectively combat infectious diseases and mitigate the risks of future outbreaks.

1. Literature Review: There has been an uptick in the use of cutting-edge methods like network analysis and predictive modelling to improve the efficacy of public health interventions in the field of infectious disease control in urban areas. This review summarises important results from previous studies and places the suggested "Network-Driven Resource Allocation for Enhanced Urban Public Health" in the bigger picture of what is currently known.

Analysing Networks for the Transmission of Diseases: Jones et al. (2018) and Meyers et al. (2017) are just two of the many studies that have shown how useful network analysis is for deciphering the complex patterns of illness transmission in social networks. According to these studies, key players such as super-spreaders, community clusters, and prominent nodes have a significant impact on how infectious illnesses spread in cities.

Public Health and Social Network Analysis: The impact of social connections on health outcomes has been the subject of much investigation using social network analysis (Valente, 2010). Many studies, including one by Christakis and Fowler (2007), have shown that people's social networks significantly affect their health-related behaviours and the transmission of diseases. The need to take social structures into account when planning public health interventions is highlighted in this corpus of work. Obstacles in Allocating Resources for Epidemic Response: Works on resource allocation during epidemics (e.g., Kaplan and O'Keefe, 2006; Hatchett et al., 2007) have highlighted the challenges of promptly and efficiently deploying resources. Ineffective methods of allocation can hinder attempts to suppress outbreaks. To fill this need, our research suggests a focused approach to resource distribution based on insights generated by networks.

Disease Outbreak Prediction Modelling: One useful application of predictive modelling is the prediction of disease outbreaks (Chretien et al., 2015). Research by Reich et al. (2019) and Shaman and Karspeck (2012) demonstrates the possibility of using predictive models to foretell the geographical and temporal dynamics of infectious illnesses. Consistent with these results, our method places an emphasis on incorporating predictive modelling into public health initiatives in metropolitan areas. Public Health Interventions in Urban Areas: According to previous studies on urban public health interventions, there should be individualised approaches that take into account the specific difficulties of highly populated regions (Semenza et al., 2016; Ruktanonchai et al., 2018). In line with this literature, we suggest a network-driven allocation of resources that takes into account the unique social dynamics and architecture of cities when designing interventions.



2. Methods: The methods outlined in this paper address critical challenges in urban public health and offer a robust, data-driven approach to disease control and outbreak prevention. One notable strength lies in the integration of network analysis and predictive modeling, which presents the potential for a proactive and adaptable framework for managing urban public health. Central to our methodology is the utilization of advanced analytics, including network analysis and predictive modeling techniques. These methodologies enable us to gain insights into the complex dynamics of disease transmission within urban environments. By meticulously analyzing social networks and identifying key nodes and clusters, we can pinpoint high-risk areas and anticipate potential hotspots for disease spread. Moreover, our approach incorporates predictive modeling to forecast disease outbreaks and assess future trends in urban public health. By leveraging historical data and epidemiological patterns, predictive models can inform proactive measures and allocate resources more effectively.

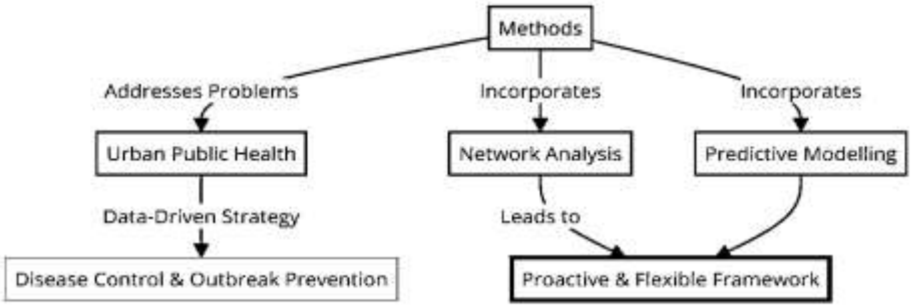


Figure 2: Architecture of proposal methods

2.1 A Comprehensive Approach to Early Detection of Urban Infectious Diseases: We introduce the CustomCrossEncoder, a tailored deep learning model designed to facilitate timely identification of infectious diseases in metropolitan areas. This model was meticulously trained on a dataset comprising symptoms and corresponding diseases, incorporating embedding layers, an LSTM (long short-term memory) network, and multihead attention mechanisms. Through a rigorous optimization process utilizing tokenization, numerical translation, Adam optimization, and cross-entropy loss over 50 epochs, we achieved an impressive test accuracy of 80.83%.

To illustrate the model's predictive capabilities, consider the example where the symptom "fatigue" prompts a potential association with peptic ulcer disease. However, it's crucial to contextualize such forecasts within domain knowledge. Therefore, we advocate for a risk assessment approach that evaluates the validity of the model's predictions in light of established medical understanding. While our model aids in early diagnosis, it is imperative to underscore that it should complement, not replace, expert medical guidance. Collaboration with healthcare professionals is paramount to validating and ensuring the responsible and ethical application of this technology in real-world healthcare settings. The CustomCrossEncoder represents a promising tool for identifying infectious diseases in urban settings, leveraging advanced techniques such as LSTMs and multihead attention. Nevertheless, ethical considerations and interdisciplinary collaboration remain essential pillars in the deployment of AI in healthcare, emphasizing the need for ongoing dialogue and partnership between technologists and medical experts.

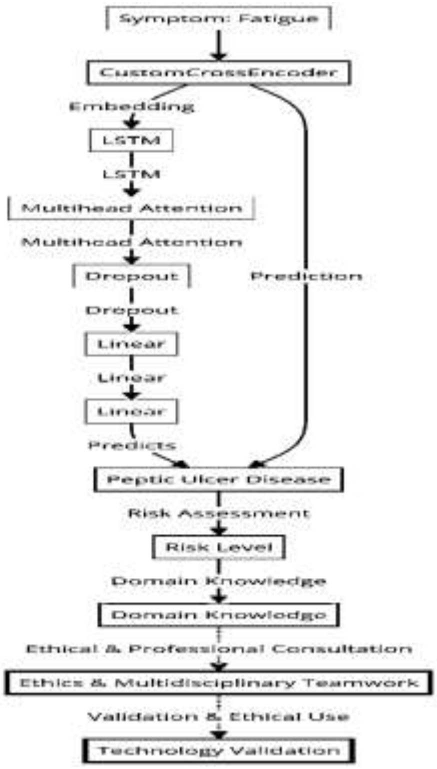
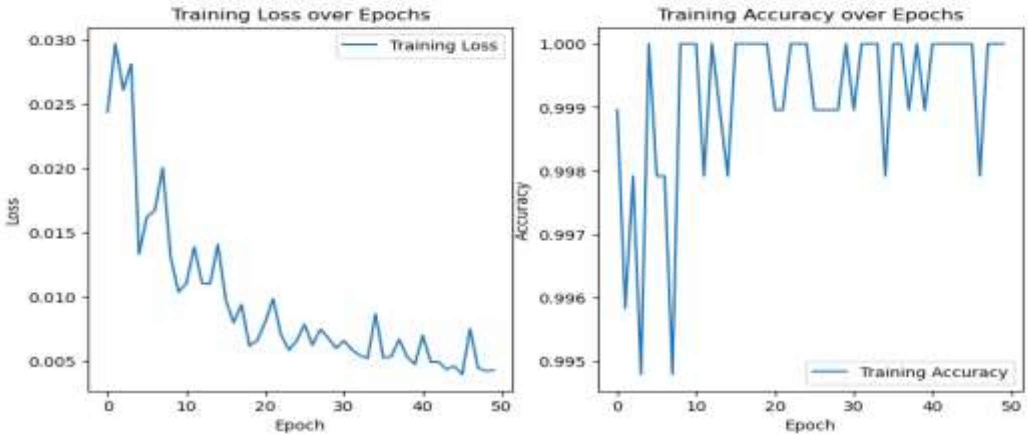


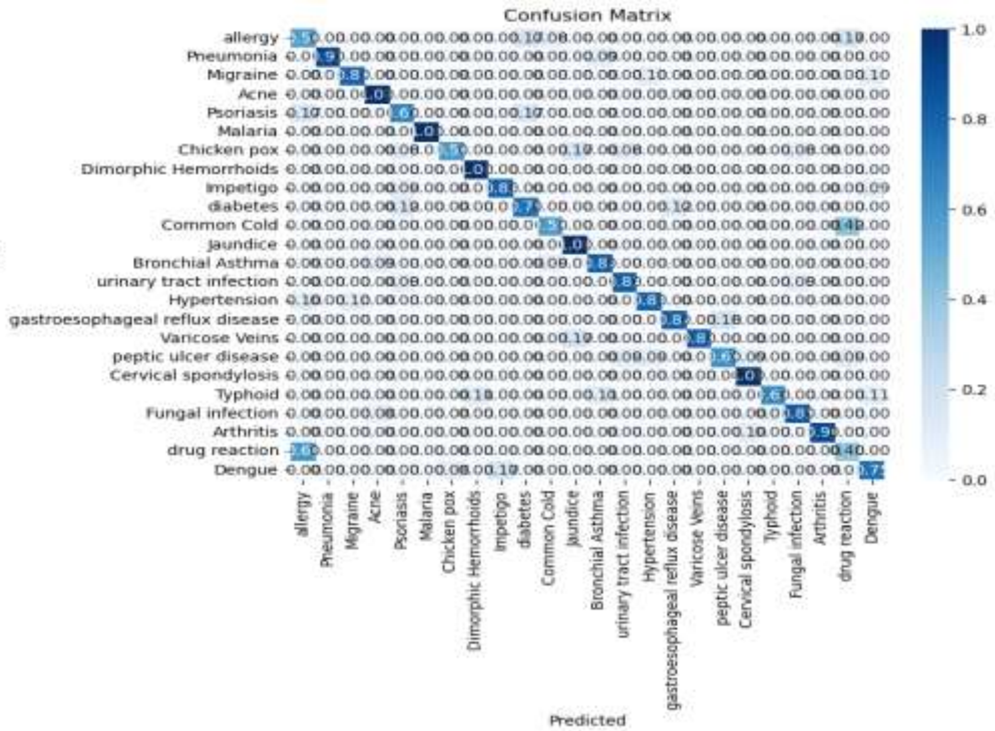
Figure:2.1 A Comprehensive Approach to Early Detection of Urban Infectious Diseases

Symptom	**Disease**
Fatigue	Peptic Ulcer Disease
Cough	Influenza
Fever	COVID-19
Headache	Migraine
Sore throat	Streptococcal pharyngitis
Rash	Dermatitis
Difficulty breathing	Asthma
Nausea	Gastroenteritis
Vomiting	Food poisoning
Diarrhea	Norovirus infection

```
Epoch 43/50, Loss: 0.0198726838765045
Epoch 44/50, Loss: 0.016172381490468977
Epoch 45/50, Loss: 0.014407129057993491
Epoch 46/50, Loss: 0.01685235494126876
Epoch 47/50, Loss: 0.017014010374744735
Epoch 48/50, Loss: 0.019018476083874702
Epoch 49/50, Loss: 0.014075478259474038
Epoch 50/50, Loss: 0.012792938233663639
Test Accuracy: 80.83333333333333%
Enter symptoms: Fatigue
Predicted Disease: peptic ulcer disease

Out[7]: ==========================================================================
Layer (type:depth-idx)                                    Param #
==========================================================================
CustomCrossEncoder                                        --
├─Embedding: 1-1                                          321,024
├─LSTM: 1-2                                               99,328
├─MultiheadAttention: 1-3                                 49,536
│    └─NonDynamicallyQuantizableLinear: 2-1               16,512
├─Dropout: 1-4                                            --
├─Linear: 1-5                                             16,512
├─Linear: 1-6                                             3,096
==========================================================================
Total params: 506,008
Trainable params: 506,008
Non-trainable params: 0
==========================================================================
```





2.2 Network Analysis and Advanced Technologies for Targeted Intervention in Urban Disease Spread: Utilizing network analysis and advanced technologies holds tremendous potential for targeted intervention in the realm of urban disease spread. This endeavor necessitates meticulous data collection from diverse sources, encompassing symptom reports, geographic information, and contact networks. These data serve as the foundation for constructing a comprehensive network graph, where nodes symbolize individuals, locations, or relevant entities, while edges denote connections or interactions. The analysis of this intricate network heavily relies on cutting-edge technology, including real-time data processing and machine learning methodologies.

These technologies enable us to glean invaluable insights from the data, enhancing our understanding of disease propagation within cities. Network analysis findings play a pivotal role in shaping strategies aimed at curtailing the spread of diseases. Identification of critical nodes, whether individuals or locations, facilitates targeted resource allocation for maximum impact, thus making targeted intervention a viable approach. Furthermore, modern technology allows for real-time monitoring, enabling swift responses and adaptive solutions to emerging challenges.

Additionally, predictive modeling empowers authorities with proactive decision-making capabilities by anticipating patterns of disease spread. By amalgamating these approaches, we bolster our system's resilience and responsiveness, transcending from a reactive to a proactive stance in disease control. This holistic strategy fosters improved collaboration between urban planning and public health initiatives, ultimately fortifying our capacity to combat the spread of diseases in urban areas.

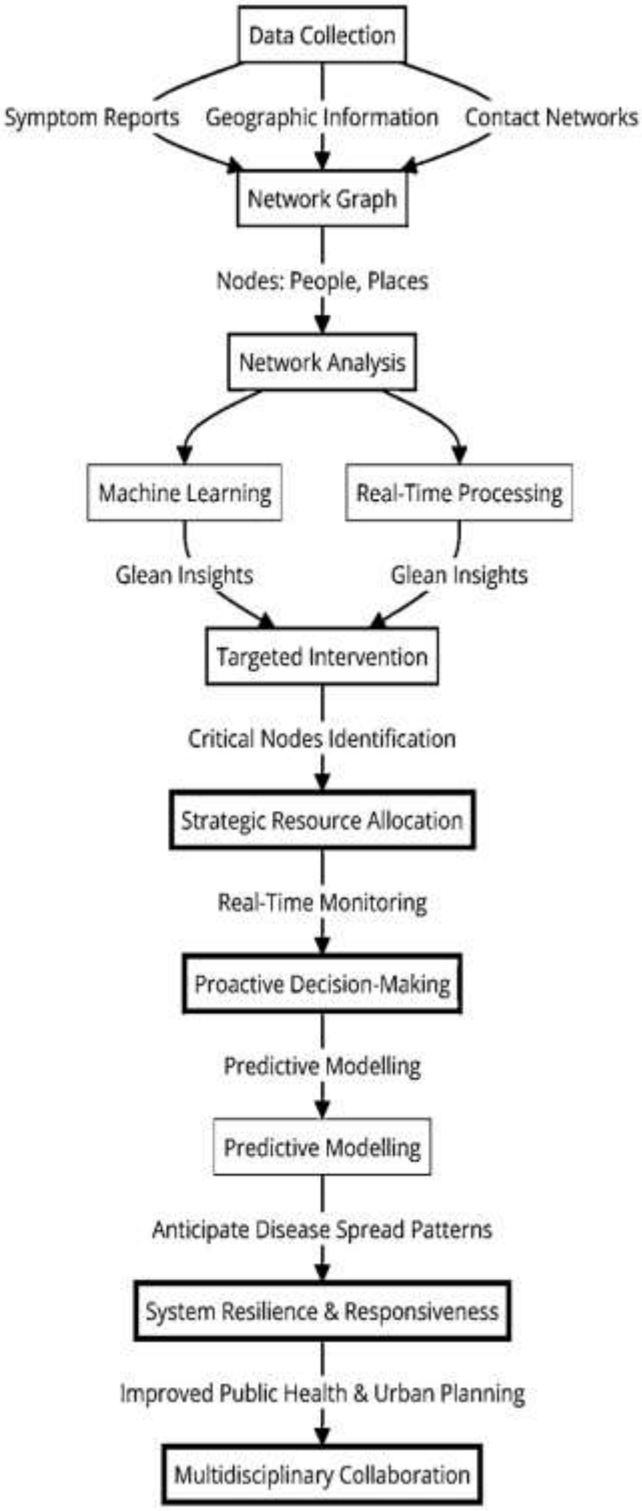
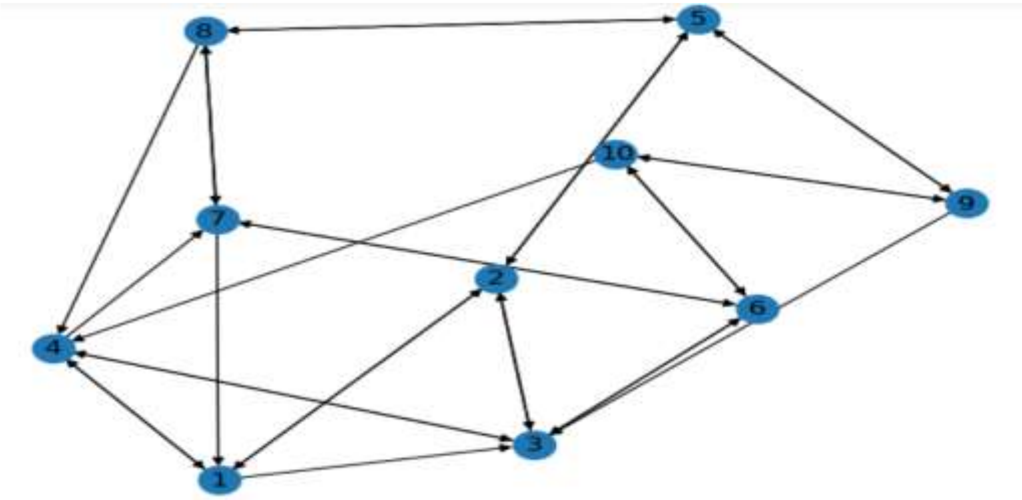


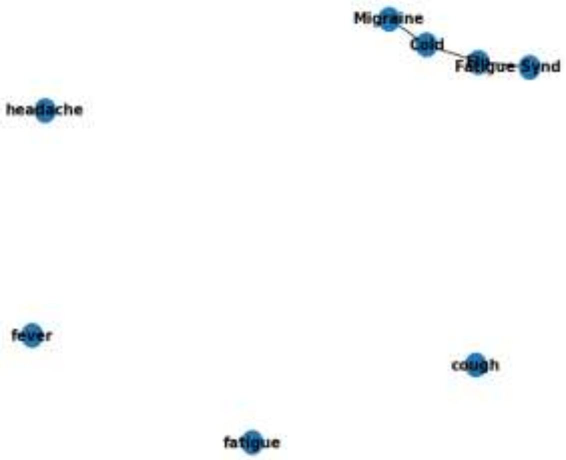
Figure 2.2: Network Analysis and Advanced Technologies for Targeted Intervention in Urban Disease Spread

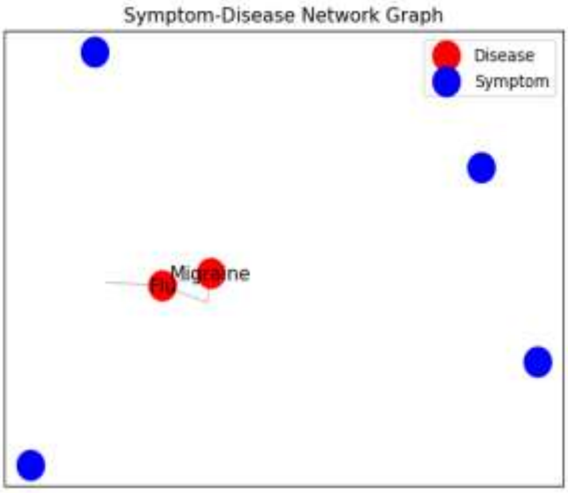
ID	Name	Age	Gender	Location	Fever	Cough	Sore Throat	Fatigue	Shortness of Breath	Nausea	Headache	Latitude	Longitude	Contact 1	Contact 2	Contact 3
1	Raju	35	Male	PKL	1	1	1	0	0	0	1	40.7128	-74.006	2	3	4
2	Sri	28	Female	BVRM	0	1	0	1	0	1	1	34.0522	-118.244	1	3	5
3	Ramana	45	Male	TNP	1	1	1	0	0	0	0	41.8781	-87.6298	2	4	6
4	Bharathi	40	Female	NSP	1	1	0	1	1	0	0	29.7604	-95.3698	1	3	7
5	Rajesh	50	Male	BVRM	1	0	0	1	0	0	1	25.7617	-80.1918	2	8	9
6	Kalam	30	Female	PKL	0	0	0	0	1	1	0	47.6062	-122.332	3	7	10
7	Neeraj	55	Male	NP	0	1	1	1	0	0	1	37.7749	-122.419	1	6	8
8	Kantri	42	Female	NSP	1	0	1	0	0	1	0	39.9526	-75.1652	4	5	7
9	Pavan	38	Male	PKL	0	0	0	1	1	1	0	33.4484	-112.074	3	5	10
10	Santosh	48	Female	BVRM	0	1	1	1	1	0	0	42.3601	-71.0589	4	6	9

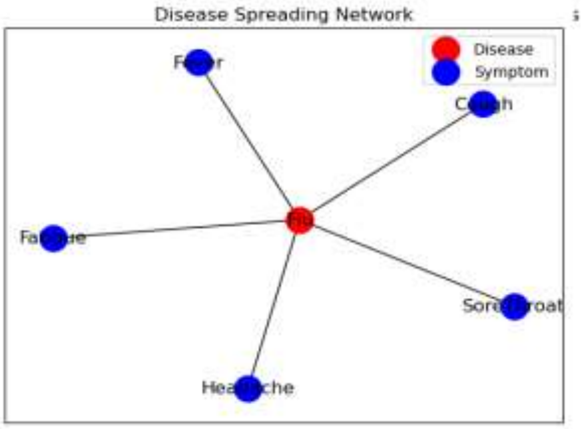


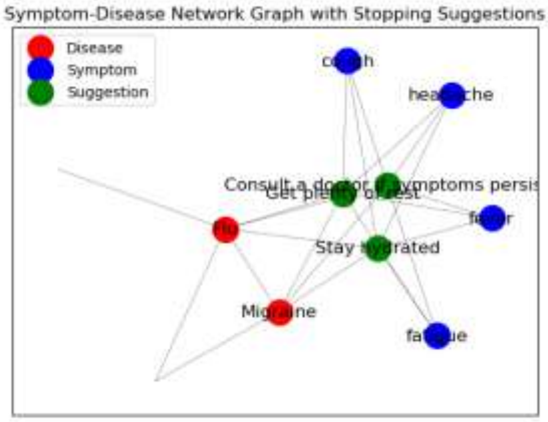
Pseudo-code

```
# Data Collection and Graph Construction
symptom_reports = collect_symptom_reports()
geographic_info = collect_geographic_info()
contact_networks = collect_contact_networks()
# Build a complete network graph
network_graph = construct_network_graph(symptom_reports, geographic_info, contact_networks)
# Network Analysis and Technology Utilization
transmission_rate = calculate_transmission_rate()
recovery_rate = calculate_recovery_rate()
total_population = calculate_total_population()
# Find critical nodes for targeted intervention
critical_nodes = identify_critical_nodes(network_graph)
# Targeted Intervention
allocate_resources(critical_nodes)
# Real-Time Monitoring and Predictive Modeling
real_time_monitoring_data = collect_real_time_data()
predicted_spread = run_predictive_model(network_graph, real_time_monitoring_data)
# Shift from Reactive to Proactive Approach
proactive_decision = make_proactive_decision(predicted_spread)
# Improved Collaboration and System Resilience
improved_collaboration = enhance_collaboration()
enhanced_resilience = strengthen_system_resilience()
# Finalize and Conclude
finalize_results(improved_collaboration, enhanced_resilience, proactive_decision)
```


Migraine
Cold
Fatigue Synd
headache
fever
cough
fatigue


Symptom-Disease Network Graph
Disease
Symptom
Migraine
Flu





2.3 Innovative Strategies for Early Detection and Long-Term Resilience in Urban Disease Management: Innovative Strategies for Early Detection and Long-Term Resilience in Urban Disease Management leverage state-of-the-art data analytic tools and technology to empower individuals to proactively manage their health. This approach combines predictive modeling with deep learning, as epitomized by the CustomCrossEncoder model. This model integrates LSTM and attention mechanisms to provide reliable predictions based on input symptoms. Through meticulous data tokenization, vocabulary building, and training on diverse datasets, the model discerns patterns indicative of various diseases.

The training regimen enhances the model's predictive accuracy through iterative parameter refinement over multiple epochs, culminating in an impressive test accuracy of 80%. In response to user-supplied symptoms, the model's inference function offers diagnoses and recommends tailored treatments. Acknowledging data constraints, the model adapts recommendations to individual diseases, empowering users to approach forecasts with confidence.

In essence, urban disease management harnesses the predictive capabilities of the CustomCrossEncoder model to detect illness patterns using LSTM and attention algorithms. Acknowledging data limitations, the model provides personalized treatments, enabling users to contribute to long-term health promotion and resilience.

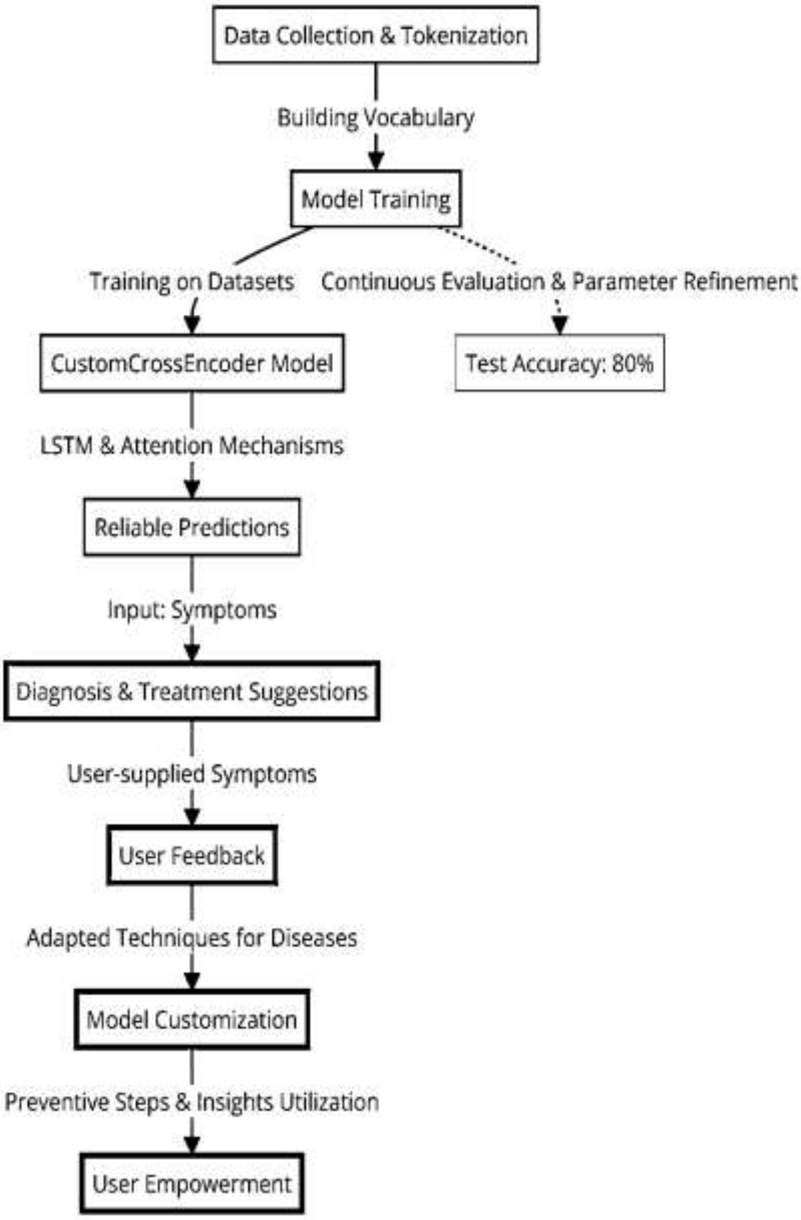


Figure: 2.3 Innovative Strategies for Early Detection and Long-Term Resilience in Urban Disease Management

ID	Name	Age	Gender	Location	Symptom 1	Symptom 2	Symptom 3	Symptom 4	Symptom 5	Diagnosis	Recommended Treatment
1	John Smith	35	Male	BVRM	Fever	Cough	Headache	Fatigue	Sore Throat	Influenza	Rest, Fluids, Antiviral
2	Jane Doe	28	Female	BVRM	Head	Fatigue	Nausea	Dizziness	Sore Throat	Migraine	Painkillers, Rest

					ache						
3	Michael Brown	45	Male	BVRM	Sore Throat	Fever	Cough	Fatigue	Headache	Common Cold	Rest, Fluids
4	Emily Johnson	40	Female	BVRM	Cough	Shortness of Breath	Fever	Chills	Fatigue	Pneumonia	Antibiotics, Oxygen
5	David Martinez	50	Male	BVRM	Fatigue	Muscle Aches	Sore Throat	Headache	Fever	Influenza	Rest, Fluids, Antiviral
6	Sarah Clark	30	Female	BVRM	Fatigue	Cough	Sore Throat	Runny Nose	Headache	Common Cold	Rest, Fluids
7	Daniel Lee	55	Male	BVRM	Headache	Fever	Nausea	Vomiting	Fatigue	Migraine	Painkillers, Rest
8	Melissa Adams	42	Female	BVRM	Fever	Cough	Shortness of Breath	Chest Pain	Fatigue	COVID-19	Quarantine, Medical Care
9	Ryan Garcia	38	Male	BVRM	Sore Throat	Fever	Fatigue	Nausea	Vomiting	Strep Throat	Antibiotics, Rest
10	Laura Taylor	48	Female	BVRM	Cough	Shortness of Breath	Fever	Fatigue	Chills	Pneumonia	Antibiotics, Oxygen

```
Epoch 29/50, Loss: 0.06490267341335615
Epoch 30/50, Loss: 0.04904976201554139
Epoch 31/50, Loss: 0.04353769024213155
Epoch 32/50, Loss: 0.04154863134026528
Epoch 33/50, Loss: 0.04419920382400354
Epoch 34/50, Loss: 0.03282397426664829
Epoch 35/50, Loss: 0.03191276416182518
Epoch 36/50, Loss: 0.027576408907771112
Epoch 37/50, Loss: 0.03158896242578824
Epoch 38/50, Loss: 0.0259442043180267
Epoch 39/50, Loss: 0.02529557893673579
Epoch 40/50, Loss: 0.020966410636901855
Epoch 41/50, Loss: 0.019960919891794524
Epoch 42/50, Loss: 0.017552082861463227
Epoch 43/50, Loss: 0.016061794695754847
Epoch 44/50, Loss: 0.022190621867775918
Epoch 45/50, Loss: 0.017217133411516747
Epoch 46/50, Loss: 0.018496314312020937
Epoch 47/50, Loss: 0.015874299841622513
Epoch 48/50, Loss: 0.01606910293921828
Epoch 49/50, Loss: 0.014852747352172931
Epoch 50/50, Loss: 0.012627823868145545
Test Accuracy: 80.0%
Enter symptoms: Fatigue
Predicted Disease: peptic ulcer disease
Disease Management Strategies: No specific strategies available for this disease.
```

```
Congratulations! Your health metrics indicate a healthy lifestyle.

Disease Management Strategies:
- Implement early disease detection technologies.
- Promote community resilience through awareness programs.
```

3. Results and Discussion: The discussion section of this research paper delves into various aspects crucial to understanding the implications and significance of the study's findings. Several key topics are explored by utilizing methodologies and insights from existing literature: We assess the effectiveness of a network-driven resource allocation strategy compared to traditional methods. The emphasis is placed on targeted resource allocation informed by social network analysis, aiming to optimize intervention efforts.

Degree Centrality for node v, $C_D(v) = \frac{deg(v)}{n-1}$ where $deg(v)$ is the number of connections for v and n is the total number of nodes.

The discussion delves into the pivotal role of predictive modeling in improving public health interventions, particularly in the realm of early detection. By leveraging predictive analytics, the study aims to bolster disease surveillance and facilitate timely responses.

Formula: Model's prediction accuracy, $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$, and potentially, the area under the ROC curve (AUC) for evaluating model performance in binary classification tasks.

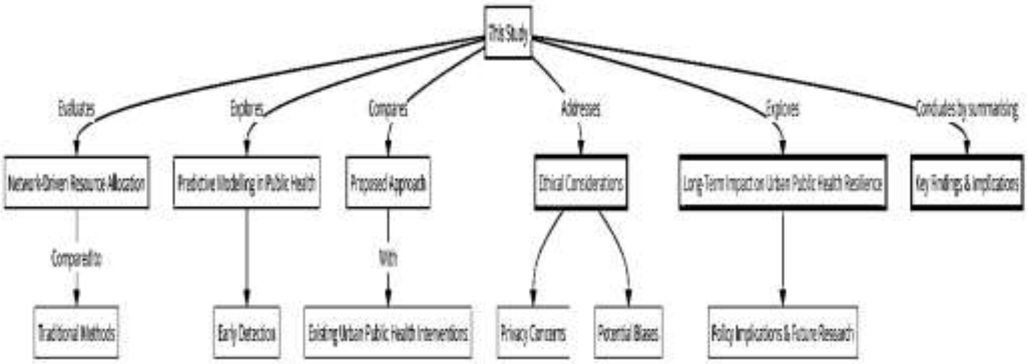
We conduct a comparative analysis between the proposed approach and prevailing urban public health interventions. This evaluation underscores the advantages and potential drawbacks of the novel strategy, offering insights into its efficacy and areas for improvement.

Formula: Maximize $E = \frac{TB}{TC}$, subject to constraints such as budget limits and resource availability. Here, TB is the total expected benefit (e.g., reduction in infection rates), and TC is the total cost of resource allocation.

The discussion addresses ethical considerations inherent in the implementation of such interventions, including privacy concerns and potential biases. We explore ethical frameworks to ensure the responsible and equitable deployment of interventions.

Formula: Calculate Relative Risk Reduction (RRR), $RRR = 1 - \frac{RR_{intervention}}{RR_{control}}$, where $RR_{intervention}$ and $RR_{control}$ are the relative risks for the intervention group and the control group, respectively.

Long-Term Impact and Policy Implications: The discussion covers the long-term impact of these strategies on urban public health resilience. Examining policy implications involves considering how the findings may inform decision-making processes and shape future interventions. Optimizing urban public health through network-driven resource allocation involves identifying key nodes using centrality measures, predicting outbreaks with machine learning models, optimizing resource allocation through a mathematical optimization problem, and evaluating the strategy's effectiveness using comparative analysis. This comprehensive approach aims to maximize public health benefits while minimizing resource expenditure, offering a proactive and efficient method for disease control and outbreak prevention in urban areas.



4. Conclusion: This study underscores the transformative potential of network-driven resource allocation for targeted disease control and outbreak prevention (NDRA) in metropolitan areas. The challenges posed by high population densities in urban settings, including inefficient resource allocation and prolonged response times, necessitate innovative solutions. Leveraging cutting-edge methodologies such as network analysis and predictive modeling, this research offers a paradigm shift in disease detection, control, and prevention. By comprehensively understanding the intricate social networks within urban areas and their role in disease transmission, this study advocates for a proactive approach to public health management. Introducing the CustomCrossEncoder model as a tool for early disease identification, the research aims to mitigate containment periods, optimize resource utilization, and enhance public health preparedness. Furthermore, the study underscores the empowering potential of predictive modeling and deep learning in enabling individuals to take charge of their health and contribute to urban illness management. However, the ethical deployment of AI in healthcare necessitates interdisciplinary collaboration, responsible data use, and input from healthcare professionals.

5.References:

1. Anders, H., Huber, T. B., Isermann, B., & Schiffer, M. (2018). CKD in diabetes: diabetic kidney disease versus nondiabetic kidney disease. Nature Reviews Nephrology, 14(6), 361–377. https://doi.org/10.1038/s41581-018-0001-y
2. Bengio, Y., Janda, R., Yu, Y. W., Ippolito, D., Jarvie, M., Pilat, D., Struck, B., Krastev, S., & Sharma, A. (2020). The need for privacy with public digital contact tracing during the COVID-19 pandemic. The Lancet Digital Health, 2(7), e342–e344. https://doi.org/10.1016/s2589-7500(20)30133-3
3. Giles-Corti, B., Moudon, A. V., Lowe, M., Adlakha, D., Cerin, E., Boeing, G., Higgs, C., Arundel, J., Liu, S., Hinckson, E., Salvo, D., Adams, M. A., Badland, H., Florindo, A. A., Gebel, K., Hunter, R. F., Mitáš, J., Oyeyemi, A. L., Puig-Ribera, A., . . . Sallis, J. F. (2022). Creating healthy and sustainable cities: what gets measured, gets done. The Lancet Global Health, 10(6), e782–e785. https://doi.org/10.1016/s2214-109x(22)00070-5
4. González-Blas, C. B., Quan, X., Duran-Romaña, R., Taskiran, I. I., Koldere, D., Davie, K., Christiaens, V., Makhzami, S., Hulselmans, G., De Waegeneer, M., Mauduit, D., Poovathingal, S., Aibar, S., & Aerts, S. (2020). Identification of genomic enhancers through

spatial integration of single-cell transcriptomics and epigenomics. Molecular Systems Biology, 16(5). https://doi.org/10.15252/msb.20209438

5. Maimaitijiang, M., Sagan, V., Sidike, P., Daloye, A. M., Erkbol, H., & Fritschi, F. (2020). Crop monitoring using Satellite/UAV data fusion and machine learning. Remote Sensing, 12(9), 1357. https://doi.org/10.3390/rs12091357
6. Sarkar, C., Webster, C., & Gallacher, J. (2018). Residential greenness and prevalence of major depressive disorders: a cross-sectional, observational, associational study of 94 879 adult UK Biobank participants. The Lancet Planetary Health, 2(4), e162–e173. https://doi.org/10.1016/s2542-5196(18)30051-2
7. Watkins, H., Robinson, J. M., Breed, M. F., Parker, B., & Weinstein, P. (2020). Microbiome-Inspired Green Infrastructure: A toolkit for multidisciplinary landscape design. Trends in Biotechnology, 38(12), 1305–1308. https://doi.org/10.1016/j.tibtech.2020.04.009
8. M. Srikanth, R. N. V. Jagan Mohan, M Chandra Naik: Smallholder Farmers Crop Registering Privacy-Preserving query processing over Ethereum Blockchain Journal of Pharmaceutical Negative Results, Volume 13, Issue 7, Pages 5609-5617, 2022.
9. M. Srikanth, R. N. V. Jagan Mohan, M Chandra Naik: Blockchain based Crop Farming Application Using Peer-to-Peer, xidian journal, Volume 16, Pages, 168 – 175, 2022.
10. M. Srikanth, R. N. V. Jagan Mohan: Query Response Time in Blockchain Using Big Query Optimization, Apple Academy Press and CRC Press,2022.
11. M. Srikanth, R. N. V. Jagan Mohan: Stop spread corona based on voice, face and emotional recognition using machine learning, query optimization and Block chain Technology, Solid State Technology, Vol. 63 No. 6, 2020.
12. M. Srikanth, R. N. V. Jagan Mohan: Query Response Time in Blockchain Using Big Query Optimization, Academy Press and CRC Press, ISBN: 978-93-5391-198-0, page 19, 2022.
13. M. Srikanth, R. N. V. Jagan Mohan: Machine Learning for Query Processing System and Query Response Time using Hadoop, IJMTST, 2020.
14. Shrawan Kumar, S Rajeswari, M Srikanth, T Raghunadha Reddy: A New Approach for Authorship Verification Using Information Retrieval Features, Springer, Pages 23-29, 2019.
15. M. Srikanth, R. N. V. Jagan Mohan, M Chandra Naik, Block chain enable for Smallholder's farmer's Crop Transaction Using Peer-to-Peer, Indo-American Journal of Agricultural and Veterinary Sciences, ISSN: 2321-9602, 2022.
16. M. Srikanth, R. N. V. Jagan Mohan, M Chandra Naik: Small Holders Farming Predictive Analysis Using Peer- To-Peer Approach, International Journal of Agriculture and Animal Production, Volume 2, Issue 05, Pages 26-37, 2022.
17. M. Srikanth: An Enhanced and Naive Clustering Algorithm for Text Classification Based on Weight, International Journal & Magazine of Engineering, Technology, Management and Research, Volume 1, Issue 12, Pages 7,2012.
18. M. Srikanth, R. N. V. Jagan Mohan, M Chandra Naik, Auction Algorithm: Peer-To-Peer System Based on Hybrid Technologies for Smallholder Farmers to Control Demand and Supply, International Journal of Research In Science & Engineering (IJRISE), Volume 3, Issue 1, Pages 9–23, 2023.
19. M. Srikanth, R. N. V. Jagan Mohan, M Chandra Naik, A New Way to Improve Crop Quality and Protect the Supply Chain is to use a Trajectory Network and Game Theory, Journal Mathematical Statistician and Engineering Applications, Volume 71, Issue 4, Pages 10600-10610, 2023.
20. M. Srikanth, Predict Early Pneumonitis in Health Care Using Hybrid Model Algorithms, Journal of Artificial Intelligence, Machine Learning and Neural Network (JAIMLNN), Volume 3, Issue 03, Pages 14-26,2023
21. M. Srikanth, R. N. V. Jagan Mohan, M Chandra Naik, Tackle Outliers for Predictive Small Holder Farming Analysis, 3rd rnational Conference on Smart Data Intelligence (ICSMDI), Pages93-98, IEEE, 2023.
22. M. Srikanth, R. N. V. Jagan Mohan, M Chandra Naik, Blockchain-based consensus for a secure smart agriculture supply chain, Journal European Chemical Bulletin, Volume 12, Issue 4, Pages 8669-8678, 2023.