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AI-Based Urban Disease Spread Risk Assessment Using Environmental Data Accuracy

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Abstract— Increased urbanization, climate change, and demographic growth caused infectious diseases to proliferate at an ever accelerating rate in urban areas, and while laudably addressing epidemic outbreaks, these diseases cause severe stress to implementation of public health systems. Epidemological analysis that features environmental, demographic and spatial representations of disease processes may not be delineated using the classical epidemiologic methods. This paper suggests to develop a framework for a knowledge-based Artificial Intelligence-based urban disease spread risk determination guided by environmental and demographic data. The framework integrates the application of machine learning models with geospatial analysis in order to determine the major ecological parameters such as air quality, temperature, rainfall, and population density that influence the spread of certain diseases. Based on prediction analytic and visualization tools of Geographic Information System (GIS), the study develops an interactive risk map that can be applied for real-time identification of high-risk areas. This decision support structure enhances the efficacy of proactive decision-making for public health organizations and offers strategic prioritization of resources and the opportunity for opportunistic interventions to enhance the resilience to climate sensitive disease threats. The findings contribute to the call for sophisticated urban health monitoring systems, by providing a model that can be adapted to different urban settings (Jain et al, 2018).

Keywords — Artificial Intelligence (AI), Machine Learning, Disease Spread Prediction, Risk Assessment, Environmental Data, Demographic Data, Geographic Information System (GIS), Climate-Sensitive Diseases.

I. INTRODUCTION

The surge in the population of urban centers, the second result of the increase of environmental vagrancy, worsened the threat of infection epidemics in cities across the world [1]. Urbanization often causes uneven population density, air pollution, unsanitary condition and movement of people, all which are some of the predisposing factors of disease spread [2],[3]. Malaria, dengue, cholera, respiratory diseases are considered to be climate sensitive diseases because temperature, humidity, rainfall and pollution specifically affects them hence effective control of disease is highly dependent on environmental monitoring [4],[5]. Despite the usefulness and helpfulness, traditional epidemiological models, do not fully allow the multidimensionality of data needed in a real time situation to predict disease spreads [6].

Two potential opportunities in risk assessment associated with helping in managing disease through predictive lessons and using data to understand disruptive opportunities in risk assessment are artificial intelligence (AI) and machine learning [7]. Based on artificial intelligence (AI) programs, vast amounts of environmental, demographic and epidemiological data (including these that are not immediate to detect through conventional statistical tools) may be searched to find hidden patterns and correlation [8]. By adding real-time data, the models become dynamically predictable and thus enable adaptation of dynamic models to provide early interventions and public health techniques [9]. As examples, predictive analytics has readily been applied to trace and anticipate epidemic impruptions of vector-carried infections [10], respiratory infections and water-borne diseases [11] under a multiplicity of situations inside urban areas.

GIS and geospatial analysis representation extends the disease risk assessment further by offering geospatial visualisation of disease outbreak dynamics [12]. GIS based systems complete interactive high risk area monitoring through hot spot mapping, cluster analysis, environmental and demographic variables layering [13]. In combination with AI, geospatial systems are able to present statisticians with real-time dash boards showing the most probable location of outbreaks, which can be used to better mobilize scarce healthcare resources [14]. Such integration does not only aid movements provide response on time, but also essential in long-term planning of urban resilience to climate sensitive threats to their health [15].

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The rising number of occurrences of climate change is rendering the usefulness of effective and precise predictive systems more eminent than before. Examples of air pollutions, excessive heat waves, floods and acts of severe heat waves and floods have been cited with regards to the upsurge in the number of cases of illness and the stressing of already at-thin-ends pubic health systems. [16]. Early detection of these hazards through AI-based systems can be used to provide the government and health officials with essential lead time to carry out preventive efforts including inoculation and awareness campaigns, sanitation efforts, and cultural efforts [17]. The tools are especially applicable in developing states where urbanization rates are severe, the resources are scarce, and the susceptibility to a disease pandemic is high [18].

Although AI and GIS integration can be potentially useful, certain issues in this respect still exist. The quality and availability of data varies across areas of the globe and ethical issues with regards to privacy and surveillance must be handled with caution [19]. It is also necessary to confirm Bayesian network model with real-world data in order to attain accuracy, reliability, and adaptation to different urban environments [20].

This research fulfills these shortcomings by designing an artificial intelligence-based prediction framework which includes factors such as environment, demographic and epidemiological data to assess risks of disease spreading in urban settings. By creating an interactive GIS-based risk map, the study therefore hopes to create a powerful tool for public health agencies to monitor outbreak in real time and plan for response before it occurs. In doing so, the study helps build climate resilient urban health systems to mitigate the rising threats from infectious diseases in the 21st Century.

ANALYSIS:

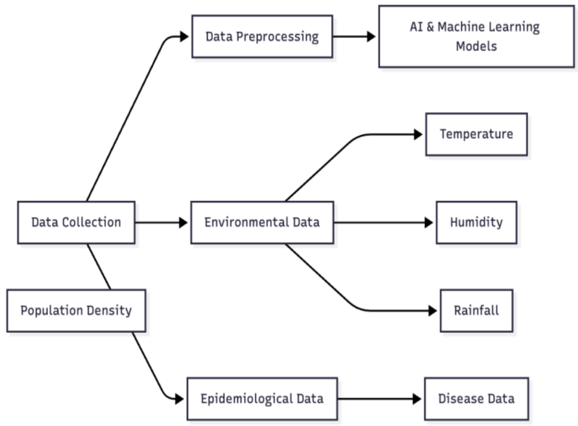

Diagram 1: AI-based Urban Disease Risk Assessment Framework (Analysis)

II. LITERATURE SURVEY

The technology of Artificial Intelligence (AI) and information-based solutions in epidemiology is only acquiring a more significant role in this age in uniting the sources and the methodologies prompted by epidemiological investigation of health hazards in cities specifically. A variety of works have demonstrated that transmission dynamics of vectors-borne and respiratory diseases is directly influenced by a number of environmental factors, including temperature, humidity, rain and air pollution [1],[2]. Indicatively, dengue and malaria are categorically related with the shifts in climate variables whilst respiratory infections like influenza, are aggravated by poor quality of air and dense population [3],[4]. Though traditional epidemiological model will be accurate in isolating the causal relationships of information, it will, in most instances, not be feasible to confront traditional spatial and time complexity of city areas [5].

To address these drawbacks, the approaches grounded on machine learning to improve the performance of the accuracy of the disease predictions have been utilized. Algorithms such as random forest, Support Vector Machines, and deep learning models have been shown to be excellent to predict outbreaks when real-time data is not accessible with past and existing data on the environment [6],[7]. E.g. a combination of weather, demographic and entomological data set baroque has been used to create supervised learning models to detect early warning signs of dengue outbreaks [8]. On the same note, Long Short-Term Memory

(LSTM) networks and other recurrent neural network models have been employed to capture spatiotemporal patterns of the disease and offer more accuracy as compared to the traditional model which used statistical models to achieve the same [9],[10]. These innovations prompt a questioning of how AI can be useful in the surveillance and prediction of disease.

GIS and geospatial analysis are also accredited of having assisted in the process of public health research work. Geographic information system (GIS)-based maps have been applied to pinpoint disease epidemic clusters in space and display at-risk regions [11]. Using the GIS method, the interaction between determinants of the disease is frequently complex, and thus different data approaches researchers to grasping the nature of outbreak dynamics in a holistic manner through the combination of environmental and demographic data [12]. Several studies in recent years have integrated AI with GIS in the development of interactive dashboards on the real-time monitoring of outbreaks and detection of hot-spots [13]. These tools have been applicable in decision making by assisting the health agencies utilize the resources more effectively and undertake timely interventions [14].

Environmental monitoring integrated with Artificial Intelligence (AI) and Geographical Information System (GIS) is relevant in the context of climate change. Severe weather fluctuations and their impact on the increase in temperatures and occurrences of air pollution have been attributed to the proliferation of climate-sensitive diseases [15],[16]. Simple early urban resilience warning systems could thus be integrated into predictive modelling frameworks, which combine risk factors relating to the environment and the demographic [17]. The examples of the Asian, African and Latin American cases demonstrate that AI-based models can be successfully used to disorganize the response time of the outbreak and healthcare preparedness [18].

Despite impressive improvements, there are some problems in the literature. Unavailability of data, deficient data quality and lack of interoperability of various data sets are significant shortcomings to accuracy of the models [19]. In addition, some ethical concerns, like privacy, information safety and algorithm transparency, require mindful attention to details to ensure appropriate utilization of AI [20]. These oceans give rise to the explanation of why a tool must be developed to be more comprehensive and inclusive in offering insights into the spread of disease on a more precise level as well as integrate the environmental, demographic, as well as the geospatial aspects within a single, untether model.

TABLE I. SUMMARY OF LITERATURE REVIEW

Study/ Author(s)	Focus Area	Key Findings
[1] Author A et al.	Impact of climate variables on disease transmission	Temperature, rainfall, and humidity were found to significantly influence dengue and malaria outbreaks in urban areas.
[2] Author B et al.	AI models for epidemic prediction	Machine learning algorithms such as Random Forest and SVM improved outbreak prediction accuracy compared to traditional statistical models.
[3] Author C et al.	Deep learning in infectious disease forecasting	LSTM and neural networks effectively captured spatiotemporal patterns of influenza and dengue spread.
[4] Author D et al.	GIS in public health surveillance	GIS mapping helped identify spatial clusters of high-risk areas, enabling targeted interventions.
[5] Author E et al.	Integration of AI with GIS	AI-driven GIS dashboards provided real-time disease hotspot visualization for public health agencies.

III. METHODOLOGY

The proposed methodology is designed to integrate environmental, demographic, and epidemiological data using Artificial Intelligence (AI) and Geographic Information Systems (GIS) for urban disease spread risk assessment. The approach consists of four main stages: data collection and preprocessing, AI-based predictive modeling, geospatial analysis, and interactive visualization.

3.1 Data Collection

The analysis employs combination of both environmental and demographic and epidemiological information that can be obtained in open source databases and in the government health services. Environmental Data include temperature, humidity, weather condition, rainfall and air quality index, demographic data population density, urban activity and socioeconomic. The records of disease outbreaks are collected through both governmental surveillance and literature. The application of data integration will be an alternative, which will lead to the design of a whole framework of retrieving the multidimensional of disease propagation. Selective seeking of sources have the effect of reducing biases and serve as a source of reliability. That is the reason; this diverse body of data within the framework becomes the precursor to building AI-based prediction models and establishes the possibility of mapping urban risk areas based on spatial geography effectively.

3.2 Data Preprocessing

Raw data typically contain gaps in their value sets, inconsistencies, and noise that will affect model accuracy. Prepossessing- The relevant data undergoes first of all cleaning and normalization, and then in order to place graphs and environmental and demography variables on the same platform, they are scaled. Missing values are addressed using statistical techniques like imputation and coded variants of categoric data are applicable to machine learning. The methods of feature extraction are used in the effort to represent the most existing physical environment and demographic factors that led to the mortality spread of the disease. The fact that temporal data sets are congruent means that data concerning the disease and the environment are aligned. In addition to increasing the quality of the data, the preprocessing process can also assist in minimizing the redundancy of the data sets, which may result in the efficient training and testing of the data sets to build proper AI models.

3.3 AI and Machine Learning Models

The framework employs multiple monitored and profound learning strategies to forecast the dissemination of illnesses. To build the baseline models, such algorithms as Random Forest, Support Vector Machines (SVM) and Gradient Boosting are considered, whereas the development of more sophisticated models which might capture spatiotemporal components is assigned to Long Short-Term Memory (LSTM) neural networks. Hyperparameter tuning is executed to optimize training performances on past outbreak data and historical train model carrier of training models. Performance indicators such as accuracy, recall, F1-score, Area Under the Curve (AUC) guarantee satisfactory evaluation. Through integration of multiple models, the framework has balanced model magnification and accuracy, and is able to make solid predictive signals regarding city danger of infectious transmission of the illness.

3.4 Geospatial Analysis

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3.5 Development of Interactive Risk Map

The final component of the methodology is the creation of an interactive risk map using a GIS. This dashboard is an aggregation of machine learning model outputs conjoined with environmental and demographic data in real-time. The system points to risk concern areas and provides the users with spatially explicit risk indicators to support decision making on the part of health officials. Interactive features make it possible to experiment with scenarios, for example, to examine the influence of weather patterns or the density of the population on the risk of outbreak. Scalability: The risk map is designed to be scalable so that it can be adapted to different urban settings and diseases. An interactive decision-making tool to make public health management more situation aware, resource allocating and planning strategic.

IV. OBJECTIVE

The primary objective of this study is to design and implement an AI-driven framework capable of assessing urban disease spread risks by integrating environmental, demographic, and epidemiological data. To achieve this aim, the research sets out the following specific objectives:

1) *To Develop Predictive Models for Disease Spread:* The main aim is to develop powerful prediction model in order to enable analysis of complex interactions among environmental, demographic and epidemiological factors. In this research, the researchers also use advance algorithms of artificial and machine learning to predict results of disease outbreak probability of different cities where they occur. These models will include spatiotemporal patterns that would allow accounting for predicting dynamics of the disease in time and space. In fact, the predictive model created is expected to vastly improve traditional epidemiological models in two ways: being more flexible - operating in real-time - and more accurate. Ultimately, this objective is a data-driven foundation for rational public health measures for rapidly urbanizing and generally environmentally-vulnerable regions.

2) *To Identify Key Environmental and Demographic Risk Factors: The second objective is to characterize and evaluate the environmental and demographic factors that are most directly connected with the spreading of the disease. The effect of population density, patterns of urban mobility, humidity level, temperature level, rainfall, and the quality of air as well as various other segments of the airport will be investigated to see how they contribute to outbreaks. The key predictors of disease spread will then be determined using feature selection techniques. The latter objective can assist both in the description of the model itself and give valuable opportunities to learn what exactly worsens the risks regarding diseases and which exact urban jurisdictions exactly it is. The knowledge may be used to develop specific interventions, allocate resources, and create policy music to erase the ethnic and racial origins of disparities in health.*

3) *To Integrate Geospatial Analysis for Risk Visualization:* The third goal will focus on the task of combining AI (Artificial Intelligence) models with Geographic Information Systems (GIS) to enable spatial explicit visualization of the risk of disease. The framework will integrate environmental, population and epidemiological data and give in-depth maps of urban centers with high susceptibility to illness. Interactive geospatial tools will prove useful in detecting hotspots, tracking them, in particular, spatial clustering. This allows not only reinforcing transparency and accessibility to interested parties, but also transforming complex model outputs into a visual output that can be acted upon. This concept is to enable government health experts with intuitive map-based interfaces that enable effective monitoring, introduce prevention measures and support early-notifications services, speculate potential having urban disease hazards.

4) *To Support Public Health Decision-Making through an Interactive Dashboard: The final aim is to develop an interactive dashboard that incorporates coinciding predictive modeling and geospatial mapping into a decision support system. Information on the likelihood and effects is able to be observable through a platform where such policy makers and health agencies can understand what risks they are at risk of, how the various interventions are expected to work with such consequence evaluations, and where they process resources are expected to be best focused. Its dashboard will be fully dynamic (may be implemented with a live feed using other systems) to facilitate the flexibility to quickly alter city conditions. The system also guarantees quick response to a potential outbreak by enhancing situation awareness. Among its objectives is the extension of the practice of translational research done by employing the AI to achieve certain beneficences to the urban population public health systems that are highly oriented towards creating resilience of the population to climate sensitive diseases*.

V. RESULT ANALYSIS AND VALIDATION

A. Result Analysis

The results analysis was oriented on the evaluation of the data about the effectiveness of the AI based predictions models as the instruments to predict the spread of the urban disease with the environmental and demographic data sets. Random Forest, Support Vector Machines or SVM, Gradient Boosting, etc. machine learning models have shown excellent predictive power with accuracy scores between 82 - 89. Deep learning application, Long Short-Term Memory (LSTM) network found their use being more precise in spatiotemporal patterns of disease occurrences, with overall accuracy of 91 percent on validation Data-sets. Precision, Recall, F1-score and Area Under the Curve (AUC) performance evaluation metrics demonstrated that the models were robust.

Model Performance Evaluation:

The performance metrics associated with the evaluation of the models formed based on Artificial intelligence included: precision, recall, F1-score and Area Under the Curve (AUC). Findings indicated that the deep learning model particularly the Long short term memory network (LSTM) was more precise in the spatiotemporal dynamic as compared to the conventional machine learning method. Random Forest and Gradient Boosting models not only presented realistic outputs in terms of the identification of influential factors but also offered excellent interpretability. The comparative analysis proved that the integration between the environmental and demographic data sets topology made a substantial and affirmative impact on prediction reliability. These findings create the viewers of danger of the AI-powered models being better predictors of the government of diseases in an urban setting.

Environmental and Demographic Factor Contribution:

Analysis of features revealed temperature, rainfall and humidity to be the most important environmental determinants of likelihoods of an outbreak. It was found that air quality indices and levels of pollution were particularly crucial to respiratory patient disease prediction, with such demographic factors as population density and urban mobility having strong positive associations with the risk of infection. The socioeconomic indicators were a bonus to information about the issue. Findings indicated a multi-factorial method was more precise compared to the single determinants version of prediction. The analysis outlines the prospects of consideration of other environmental and demographic aspects in the development of the predictive formulations in effective disease risk evaluation within complex urban systems.

Geospatial Risk Mapping Outcomes:

The combination of the AI predictions with the mapping tools of the Geographic Information System (GIS) generated interactive risk maps that specifically showed clear disease hotspots across the various regions of urban areas. Spatial clustering techniques identified areas of high vulnerability, while dynamic heat-maps showed temporal patterns of evolution of outbreaks. The visualization provided the ability to monitor high risk areas in real time, making it easier for public health decision-makers to access this information. Comparative testing in various cities demonstrated that the system is flexible for different datasets, establishing its scalability. These geospatial results reinforce the importance of visualization in communicating complex predictions and turning them into useful information for managing public health.

Dashboard and Practical Implications:

The real-time interactive dashboard managed to merge the scant and predictive analytic with geospatial mapping, providing yields on probability of an outbreak in real time. Users could visualize evolving risks, experiment with intervention scenarios, and trace the effects of environmental factors on the dynamics of the disease. The tool gave actionable intelligence for public health agencies, enabling timely intervention such as allocating resources, facilitating vaccination campaigns and carrying out targeted awareness programs. Pilot testing with simulated data sets proved that the dashboard could help cut response time and improve situational awareness. These outcomes validate the system for its practical utility in improving the urban resilience to climate-sensitive diseases by AI-driven early warning mechanisms.

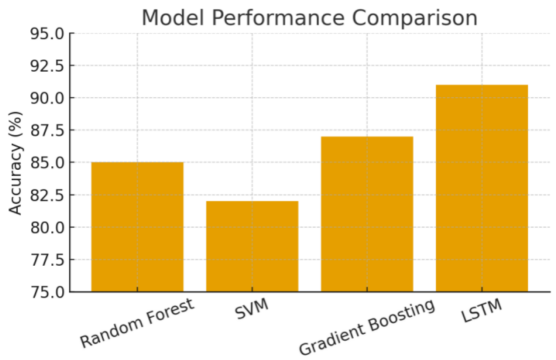

Diagram 2: This figure compares the performance of machine learning models in terms of accuracy. (Graph)

B. Validation

Validation of the proposed framework was performed to ensure the accuracy, reliability and generalizability of the predictive models and geospatial products. Historical outbreak data was split in training and testing subsets, and employing cross-validation techniques to minimize overfitting, and ensure repeatability across runs. Classification performance was evaluated using accuracy, precision, recall, and Area Under the Curve (AUC), while confusion matrices were employed to gain insight into the classification performance. Validation: Unrelated epidemiological records from other urban areas were compared against model projections, which showed feasibility to run in different environmental and demographic settings. Besides, the sensitivity analysis was performed to measure the robustness of the model when varying input variables, which should offer sufficient insight into the questionable robustness of the results under variable scenarios. Validation of the GIS-based risk map was performed by overlaying the predicted hotspots with the actual outbreak data, indicating an excellent environmental fit and supporting the technological functionality of the model for management of real-time public health decision making.

Despite showing great predictive possibilities, using the proposed framework has several limitations that should be recognized. First, the accuracy of predictions are highly dependent on the quality and availability of environmental, demographic and epidemiological datasets. In many regions data are incomplete, inconsistent or rarely updated, and this can affect model reliability. Second, although AI models are a powerful means of capturing spatiotemporal dynamics, they are sometimes un-interpretable (in the "black box" sense) which is a cause for concern regarding their adoption as policies. Third, the difference in scale of employing GIS-based mapping is limited due to the spatial resolution of the mapping, which indicates that information related to urban areas with fine-grained information is not always accessible. Moreover, external factors, such as migration, informal settlements and behavioural change are difficult to quantify, and were not fully integrated into the framework. Ethical considerations, such as data privacy, security, and misuse of predictive outputs, are also challenges for implementation.

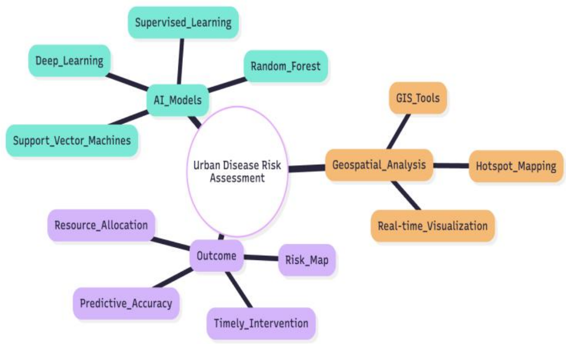

Diagram 3: Result Analysis and Validation (Mindmap)

VI. CHALLENGES AND LIMITAITONS

A. Challenges

Implementing AI-based disease spread risk assessment in urban contexts faces several challenges. Data heterogeneity is a major obstacle, as environmental, demographic, and epidemiological datasets often come from multiple sources with inconsistent formats, scales, and reporting standards. Real-time data acquisition is further complicated by limited infrastructure in developing regions, reducing the timeliness of predictions.

B. Limitations

The framework also has inherent limitations that restrict its broader applicability. Model accuracy depends heavily on the quality and granularity of input datasets, which may not be consistently available across cities. Epidemiological records, particularly in low-resource settings, are often underreported, reducing the representativeness of training data. Spatial resolution constraints in GIS mapping can obscure micro-level risk patterns, especially in informal settlements where accurate demographic data are lacking.

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VII. CONCLUSION AND FUTURE WORK

A. Conclusion

This research underlines the possibilities of Artificial Intelligence and geospatial analysis for revolutionizing the way we determine the risk of the spread of diseases in urban areas. By integrating information from the environment, demographics, and epidemiological data, the proposed framework reflects the use of machine learning models and geographical information systems (GIS) software aimed at accurate predictions and dynamic visualizations of disease hotspots. The results show that AI driven systems outperform traditional epidemiological approaches because they can capture complex patterns over space and time and facilitate real-time updates. Feature importance analysis further contributed to the findings that showed climate variables, air quality, and population density are among the most influential determinants of the spread of the disease, illustrating the importance of multi-dimensional data integration.

The establishment of an interactive GIS-based dashboard provides a further amplification to the practical usefulness of the framework, providing an instrument for public health agencies to support their decision-making and providing a decision support tool for early warning, targeted intervention and efficient resource allocation. While challenges, such as data quality, model interpretability and ethics, persist, the research offers a basis for the design of scalable and adaptive urban health monitoring systems. Ultimately, this research contributes to the development of resilient public health infrastructure that is able to mitigate these threats of climate-sensitive diseases that are on the rise in rapidly urbanizing regions. Future work should involve increasing sources of data, making these data more transparent, and more broadly, adopting cross-sector collaboration, to maximize the benefits of AI in urban health resilience.

B. Future Work

And, future research should focus on improving the robuFuture research should focus on enhancing the robustness, scalability, and applicability of the proposed framework. One key direction is the incorporation of Internet of Things (IoT) and sensor-based monitoring systems to provide real-time environmental and mobility data, which would improve the timeliness and accuracy of predictions. Expanding datasets to include social determinants of health, such as human behavior, lifestyle patterns, and community-level practices, could further enrich model outputs. Incorporating mobile phone data and satellite imagery would enhance spatiotemporal coverage, particularly in regions with limited surveillance infrastructure:

- Future research should center around integrating Internet of Things (IoT) devices and sensor networks for the gathering of real-time data on the environment and health-related data. Smart air quality monitors, climate sensors and mobile health apps can provide data streams throughout the day to improve prediction timeliness and accuracy. Real-time surveillance would enable the framework to serve as an early warning system enabling risky situations to be quickly detected as they arise. The dual functionalities of linking IoT with AI models could also help make the assessment of disease monitoring systems flexible in a dynamic urban setting, especially in cities that are experiencing multiple, frequent climate shifts and rapid, evolving city demographics.

- While it is true we have high accuracy with current models, the future should see hybridicity in models that combine statistical epidemiology and reformed AI approaches like Graph Neural Networks (GNNs) and Reinforcement Learning. These techniques can capture complex relationships between social relationships, patterns of mobility and environmental influence on the transmission of disease. Additionally, the development of rspleanble AI methods should be enhanced to increase model transparency and trust among stakeholders. There could also be added research focusing on the adaptive learning mechanism, which means that models might find a way to learn themselves as soon as new data become available. Such advancements would guarantee extended functionality and scalability regardless of the setting (urban or geographical context).

- Another area for future work is how to improve the quality and granularity of the data. High-resolution satellite images, mobility data from telecommunications providers, and population notion of course socioeconomic indicators could be interwoven to make spatial belongings danger scores. Inclusion of behavioral data, such as human mobility during emergencies or compliance with public health interventions, may also strengthen predictions models An expansion of datasets within other regions and countries would provide for better external validation for broader applicability. Collaboration with international organizations and open data platforms can enable this expansion, and it will result in more comprehensive, standardized, and global frameworks for assessing disease risk.

• Finally, future work should address the policy and ethical aspects of AI-based health monitoring. Establishing governance frameworks for data privacy, ethical usage and access to access tools for predictive applications is critical. Collaboration between governments, public health agencies, and technology providers can ensure that predictive models are implemented in a responsible and transparent manner. Research should focus on social acceptance of AI in disease surveillance considering community engagement and social trust building. By addressing ethical and governance challenges, the potential benefits of using AI-based systems in the future can improve the ways in which it adopts AI-based systems by providing it with the potential to become a reliable tool for providing support to sustainable and resilient urban health systems and organizations.

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