

AI-Powered Urban Health Monitoring Systems: Enhancing Public Health Resilience in Smart Cities

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Abstract: Public health management faced by urban environments includes many challenges such as deterioration of air quality, outbreaks of diseases, stressors on mental health which came with dense population areas making them an easy target for viral spread. AI-Powered Urban Health Monitoring Systems present a new paradigm that could revolutionize how we tackle these challenges. These systems can harness sophisticated machine learning algorithms to process massive amounts of real-time information from a variety of sources (e.g., environmental sensors, healthcare databases, social media platforms, etc.). For example, real-time air quality data can be integrated with meteorological patterns to predict pollution in advance, informing urban design and public notices. Natural language processing tools could also track social media for early signs of mental health crises, enabling more focused community support. In order to make these systems beneficial for all urban populations, the ethical implications of data privacy and equitable access must be considered at every point in the process of design and implementation. By leveraging AI, urban health monitoring can become smarter, healthier, more equipped to address the multifaceted challenges of modern urbanization. In this research, we approach, machine learning algorithm for model performance. Support vector machine (SVM) and logistic regression and Multinomial NB used as classifiers for classification. This dataset includes "Health Monitor Dataset" having 20 columns and 4286 rows. Cleaned and preprocessed data were used in our work. We conducted some training and assessment. A classifier's accuracy is measured using evaluation metrics. The Logistic regression outperform well, with the accuracy having 88.76% over the multinomial nb and support vector machine.

Keywords— Machine Learning; SVM (support Vector Machine); LR(Logistic Regression, NMB(Multinomial NB), Feature Scaling, Label encoding etc.

1. Introduction:

AI Revolutionizing Urban Health AI is transforming urban health monitoring systems, enabling better disease surveillance, environmental monitoring, and personalized healthcare. From illuminating public areas to save energy to providing smooth commute and traffic using AI algorithms with the help of IoT devices and big data analytics work towards smart cities smart health ecosystems, proactive, and effective public health management. we can see AI leading the way in smart city

planning. AI-based applications have been created to track and anticipate disease outbreaks in urban areas. These tools use data analytics to analyze information from social media, health records, and other sources to issue real-time alerts. This information is crucial for better urban planning and for associated policies aimed at minimizing environmental health risk. Integrating AI with wearable devices and remote monitoring systems has brought a new dimension to personalized health care in urban settings. The AI algorithms analyze data collected from these wearable sensors on parameters like heart rate, blood pressure, and glucose levels. A continuous monitoring system allows for timely detection of health anomalies, thus enabling effective treatment for long-term diseases and helping lighten the burden on healthcare facilities. Wearable technology, mobile health and online applications, and other personal monitoring tools offer enormous promise to enhance asthma treatment. There are already many more applications for asthma that cover health education, symptom recording, inhaler use tracking, environmental alarm display, and medication reminders. These apps can be used alone or in conjunction with sensors on inhalers. Wearable devices and remote monitoring systems integrated with AI have transformed personalized care in urban centers. AI algorithms use data from wearable sensors that measure vital signs such as heart rate, blood pressure, and glucose levels. This constant monitoring allows for the early detection of health problems and chronic disease management, thus taking the load off healthcare facilities. By a process of detection of the disease at early stages, by environmental monitoring, and by direct delivery of healthcare, artificial intelligence boosts the health of urban communities by making them healthier and more resilient. Asthma is a chronic condition found among millions of people across the globe, with some requiring proactive management and continuity of care. AI-assisted health monitoring systems provide real-time monitoring, predictive analytics, and personalized treatment advice, changing the face of asthma treatment. These systems, employing wearable devices, intelligent sensors, and ML algorithms, aim to improve patient outcomes and minimize emergency room visits.

2. Related work:

Healthcare systems in cities are using AI and data analytics to improve the quality, accessibility, and efficiency of treatment for citizens as metropolitan areas continue to expand. Smart cities are developing into centers of proactive, data-driven healthcare by combining technologies like telemedicine,

predictive analytics, IoT, and personalized medicine. Numerous domains, including mental, social, political, economic, and urban health, are linked to health. The WHO states that the foundation of healthy urban planning is planning for people. It comprises putting the requirements of the community and people first during the urban planning process and taking into account how decisions will affect people's health and general well-being. It is comparable to sustainable development planning in that it also involves finding the right balance between the needs of the social, environmental, and economic spheres. The concept is based on the core Healthy Cities tenets of equity, intersectional cooperation, sustainability, and community involvement. From 2011 to 2021, this study examines how artificial intelligence (AI) technologies might improve the resilience of urban public health in 284 Chinese cities. Through patent applications and authorizations, the study measures AI technology levels using a comprehensive index based on resistance, recovery, and innovation dimensions. These are further broken down into invention, utility model, and design patents. To examine the direct and indirect impacts of artificial intelligence on urban public health systems, two-way fixed effects regression models and spatial econometric models are utilized. With greater effects seen in eastern and central regions as opposed to western regions, where economic and technological capacities are weaker, the results show that AI technology greatly improves resilience by enhancing resource allocation and reaction efficiency [1]. Since the population's well-being is directly related to public health services, they have become an essential part of social welfare as China moves from rapid growth to high-quality development [2]. The design, use, and initial testing findings of the device are described in this paper, highlighting its potential to enhance health outcomes by facilitating proactive asthma control. By improving people's health and well-being, this technology's implications demonstrate how it aligns with the Sustainable Development Goals. Personalized guidance and educational materials for asthma control are made easier by the incorporation of a companion app that uses large language models, such as ChatGPT [3]. Millions of people worldwide still suffer from asthma, a chronic respiratory disease that causes symptoms like coughing, chest tightness, wheezing, and dyspnoea. Lack of early warning systems for asthma attacks is a major problem in this area, especially for vulnerable populations like children under the age of twelve and people with mental illnesses like autism or Down syndrome. These populations frequently have trouble expressing their symptoms [4]. Not only are asthma attacks a major cause of hospitalization for children and people with mental disabilities, but they are also potentially fatal, which emphasizes the need for creative ways to treat this illness. These vulnerable groups face additional health risks due to the unpredictable nature of asthma flare-ups and difficulties in early identification. By enabling prompt intervention, the proposed smartwatch may decrease emergency room visits, improve illness management, and eventually raise asthmatics' quality of life. This is in line with SDG 17's focus on utilizing partnerships to drive healthcare innovation through technology, as well as the third UN Sustainable Development Goal, which

focuses on promoting well-being and ensuring healthy living at all ages [5]. Asthma is becoming more common worldwide, with children from low and middle-income nations being disproportionately affected. According to recent research, this illness affects around 339 million individuals globally, significantly impairing everyday activities, attendance at school, and general quality of life [6]. Predictive technology and monitoring systems are essential for better asthma management. Projects such as the ones outlined below have shown that it is feasible to use wearable sensors that are connected to Internet of Things systems to monitor environmental triggers like NO₂ and aldehyde levels in real time, greatly assisting in early detection and management [7]. AI systems are combined with wearable technology and home monitoring devices to continuously measure patient health data for ongoing management. By predicting possible asthma attacks using data trends, these technologies allow for preventative medical measures. AI-powered mobile health apps that offer health advice, prescription reminders, and virtual consultations with medical professionals improve patient engagement and compliance. The number and intensity of asthma episodes are decreased, and patients' quality of life is greatly enhanced by this degree of continuous, individualized monitoring [8]. A widespread chronic respiratory condition that affects 262 million people worldwide, asthma claims half a million lives annually. Poor asthma outcomes are often caused by a lack of objective diagnostic testing, poor engagement with asthma services, and non-adherence to medicine. Technological advancements in recent years have improved care, monitoring, and diagnosis [9]. They sought to present estimates of the prevalence and incidence of asthma worldwide in 2019 using the four primary epidemiological case definitions: ever asthma, current asthma, ever wheezing, and current wheezing. To ascertain the prevalence and case distributions of current wheeze and ever asthma at the regional and national levels, we also looked at the main contributing factors [10]. The impact of artificial intelligence (AI) on urban health systems in response to climate change is examined in this chapter. It looks into how AI might be used to manage health hazards related to air pollution, heatwaves, and vector-borne illnesses. In order to improve preparedness and resilience for health issues brought on by climate change. Artificial Intelligence's contributions to real-time health monitoring, personalized medicine, and predictive analytics [11]. Robotic automation, rule-based expert systems, machine learning, natural language processing, and real robots are all included in the broad category of artificial intelligence. The development of clinical devices and computerized systems for safely and effectively diagnosing, treating, and planning care is a clear indication that artificial intelligence is becoming more and more important. This study examines the use of artificial intelligence and other modern technology in smart city healthcare [12]. An innovative strategy for managing chronic diseases in rural locations is provided by AI-enhanced remote monitoring, which improves patient outcomes, increases access to healthcare, and maximizes resource use. Bridging the healthcare gap between urban and rural populations requires sustained innovation and investment

in AI technology [13]. The findings of this review demonstrate how AI-enabled RPM architectures have revolutionized healthcare monitoring applications due to their capacity to identify health problems early, customize monitoring of individual patient health parameters through federated learning, and identify patterns of human behavior through methods like reinforcement learning. The difficulties and developments in integrating AI into RPM systems, as well as implementation concerns, are covered in this article [14]. The influence and function of AI are examined in this paper, with an emphasis on RPM. According to the report, AI-supported designs in building RPM have changed, enhanced, and unveiled new potential uses and advantages for remote health monitoring [15]. This research highlights the function of machine learning in incorporating health concerns into urban design. Through the examination of diverse data sources, such as air quality statistics, transportation trends, and socioeconomic indicators, machine learning algorithms are able to pinpoint social and environmental elements that influence health outcomes. This information guides health-focused urban planning, which benefits urban dwellers' general health and well-being [16]. The purpose of this study is to list the milestone development work, provide an overview of current research trends, and suggest some future lines of inquiry for the creative use of AI in civil infrastructure health monitoring. In chronological order, a detailed summary of the significant technological advancements in this field of study is given. Each milestone publication's performance metrics, important contributions, and detailed applications are provided. To illustrate current research trends, representative technologies are described in depth [17]. The purpose of this study is to evaluate how AI-based health monitoring systems might improve chronic illnesses. When combined with artificial intelligence capabilities, smartwatches and mobile applications allow users to monitor, assess, and offer interventions on a regular basis. To evaluate the impact of AI tools on patient outcomes in a randomized controlled experiment, both quantitative and qualitative research methods were used. According to the data, the patients' blood pressure, HbA1c, and medication adherence have all improved. The CNN model has the highest accuracy and prediction out of all the models, and AI systems are more effective [18]. The relationship between urban resilience, healthcare, and the Internet of Things (IoT) in relation to emergency response systems is critically examined in this study paper. Examining how well IoT technology might improve the responsiveness and efficiency of urban healthcare in times of crisis, the study focusses on this topic [19].

3. Methodology:

The suggested approach describes a multi-layered, data-driven framework for tracking, anticipating, and managing public health issues in urban settings that combines sophisticated artificial intelligence techniques with diverse urban data sources. Accuracy, scalability, ethical compliance, and real-time responsiveness are all guaranteed by the methodology's interconnected phases.

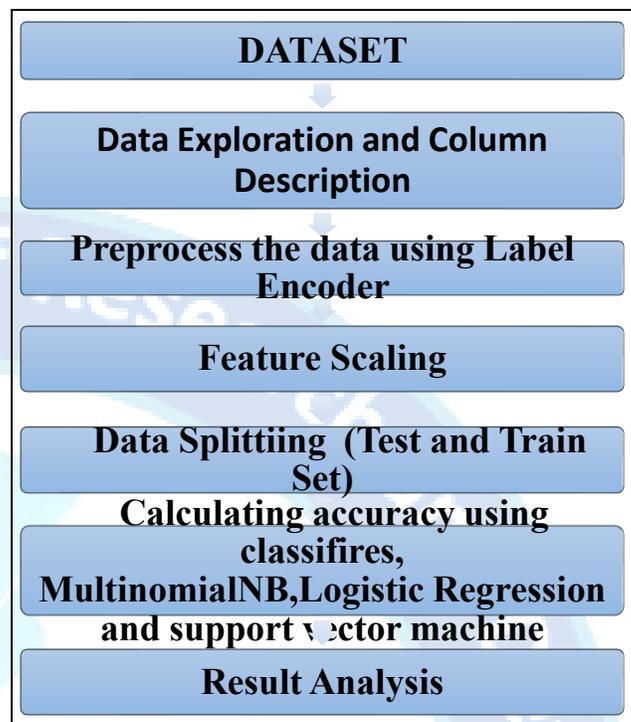


Fig 1: Standard supervised machine learning workflow

We used the “Health Monitor Dataset” in this work. It is a comma separated file(.csv). The dataset consists of .csv file which is used in this work. The dataset is set access from the website at kaggle.com. It shape of dataset having 20 columns and 4286 rows. Using this dataset, we observed that patient causes respiratory imbalance respiratory imbalance as shown in Fig. 1.

Data Exploration and Column Description:

In The Health Monitor Data columns' descriptive statistics are produced using the describe() method. It provides a brief synopsis of important statistical measures, including percentiles, mean, and standard deviation. Describe() may handle categorical data as well as numeric data by default, providing customized insights according to the data type. Data cleaning starts with a comparison to replicate, non-numeric, and null values. After the acquisition, we eliminate duplicates and non-numeric values.

Label Encoding of dataset:

In order for machine learning models that only accept numerical data to fit categorical columns, a technique called label encoding is used to transform them into numerical ones. Because it gives each category in the data a distinct integer, it can be used with machine learning models that require numerical inputs. The ability to search up a key and receive its value is known as a mapping. There are many different kinds of things that can be used as keys in mappings. In addition to being

collections, all mappings are iterable containers with a preset length.

learning algorithms such as Support Vector Machine (SVM) and Logistic Regression (LR) and Multinomial NB.

```
Health_dataset.info()
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4286 entries, 0 to 4285
Data columns (total 20 columns):
#   Column                               Non-Null Count  Dtype
---  -
0   Dehydration                           4286 non-null   bool
1   Medicine Overdose                     4286 non-null   bool
2   Acidious                              4286 non-null   bool
3   Cold                                   4286 non-null   bool
4   Cough                                  4286 non-null   bool
5   Dehydration.1                         4286 non-null   int64
6   Medicine Overdose.1                   4286 non-null   int64
7   Acidious.1                            4286 non-null   int64
8   Cold .1                               4286 non-null   int64
9   Cough.1                               4286 non-null   int64
10  Type                                   4286 non-null   int64
11  Temperature                           4286 non-null   int64
12  Heart Rate                            4286 non-null   int64
13  Pulse                                  4286 non-null   int64
14  BPSYS                                  4286 non-null   int64
15  BPDIA                                  4286 non-null   int64
16  Respiratory Rate                      4286 non-null   int64
17  Oxygen Saturation                     4286 non-null   float64
18  PH                                     4286 non-null   int64
19  Causes Respiratory Imbalance          4286 non-null   object
dtypes: bool(5), float64(1), int64(13), object(1)
```

Fig 2. Pre-cleaning data information

Feature Scaling:

We can enhance our features because of it. Machine learning algorithms that determine how to segregate data depend on it. When scaling is overlooked, features with a wider range of values begin to influence distance calculations disproportionately. The most prevalent machine learning techniques that require feature scaling include nearest neighbor, support vector machines, logistic regression, and linear regression. On the other hand, most non-linear machine learning methods, like naive Bayes, random forest, and decision trees, do not necessitate feature scaling. In these instances, training data is utilized shows in fig.3.

	Dehydration	Medicine Overdose	Acidious	Cold	Cough	Cold .1	Cough.1
0	0	0	0	1	1	1	1
1	0	1	1	1	1	1	1
2	0	0	1	1	0	1	0
3	1	1	0	0	0	0	0
4	1	0	0	1	0	1	0
...
4281	0	0	1	0	1	0	1
4282	0	0	0	0	1	0	1
4283	0	1	1	0	0	0	0
4284	1	1	1	1	1	1	1
4285	1	0	1	0	1	0	1

Fig 3: Feature scaling display

Classification Classifiers-

The next stage is to use classification algorithms after preprocessing and feature selection We employed machine

Support Vector Machine-

Creates a decision boundary that is as robust as possible by using linearly separable classes. This indicates that the position of the boundary is determined by the points nearest to it. The decision boundary is a line or hyperplane that is as far away from either class's nearest training instance as possible. The SVM algorithm is a constraint-based optimization problem with inequality constraints. To address this problem, we employed support vector machine optimization with a hard margin. For a linear SVM, the decision function is:

$$f(x) = w \cdot x + b$$

Here, w is weight vector, x is feature vector and b is bias.

Logistic Regression-

It is used when the dependent variable (target) is categorical. For binary and linear classification challenges, it is a simple and effective strategy. It's a straightforward classification model that produces outstanding results with linearly separable classes. It estimates the probability that a given input belongs to a particular class using the logistic (sigmoid) function.

The model computes a weighted sum of input features:

$$Z = \beta_0 + \beta_1x_1 + \beta_2x_2 + \dots + \beta_nx_n$$

This value is passed through the sigmoid function:

$$P\left(y = \frac{1}{x}\right) = \frac{1}{1+e^{-z}}$$

Here, P is probability of the classes $\beta_0 + \beta_1x_1 + \beta_nx_n \dots$ are model coefficient and x shows the input features.

Multinomial NB-

A popular probabilistic supervised machine learning technique for text classification problems like topic classification, sentiment analysis, spam detection, and document classification is multinomial Naïve Bayes. Based on the Bayes theorem, it makes the assumption that, given the class label, features (words) are conditionally independent. Multinomial Naïve Bayes models the frequency of words occurring in a document. It is computed given below equation where 'C' denotes class as document 'd'.

$$P(d|C) = \prod_{i=1}^n P(w_i | C)^{f_i}$$

4. Result and Discussion

We have done so to complete the experimental task. In this study, the Health Monitor Dataset was utilized for

experimentation. The dataset is provided in comma-separated values (.csv) format and was obtained from the Kaggle online repository. It comprises 4,286 records with 20 attributes, making it suitable for analyzing health-related patterns. The dataset was selected due to its structured format and relevance to the objectives of this research. Data cleaning up begins with a close look to the dataset top pick out common problems like replicate records, missing number of ideals or perhaps inconsistent non numeric posts. After retrieving the data, duplicates and irrelevant non-numerical records are eliminated to improve the overall quality of the data. Since many machine learning models can't handle categorical data, we need to convert it before formulating our model. This approach provides a unique number to each category so it can be applied efficiently. The dataset was further split into training and testing sets to evaluate model performance. Specifically, 80% of the data was allocated for training, while the remaining 20% was reserved for testing. Classification techniques follow feature selection and preprocessing. 'Causes Respiratory Imbalance' column is used as a label for the output calculation. Deals with missing value and eliminates duplicates with label encoder data. And then comes feature scaling, We employ different classifiers such as Logistic Regression(LR), Support Vector Classifiers(SVC) and Multinomial NB(MNB). The mentioned classifiers were trained to form the model for computation of the accuracy. Using these baseline functions, we generated objects that were predicted using prediction on the test set and fitted to our model on the train set using fit (). Table 1.and graph in figure 4, presents the results of the comparison between the training and testing scores. Of the three classifiers used to assess accuracy, Logistic Regression provided the best accuracy, at **88.76** percent. It demonstrated a notable improvement in the Logistic Regression classifier's accuracy value in the supervised model. Millions of unannotated texts will be useful in the future for the use of semi-supervised algorithms. The results demonstrate clear performance variation among the selected classifiers, which can be attributed to their underlying learning mechanisms

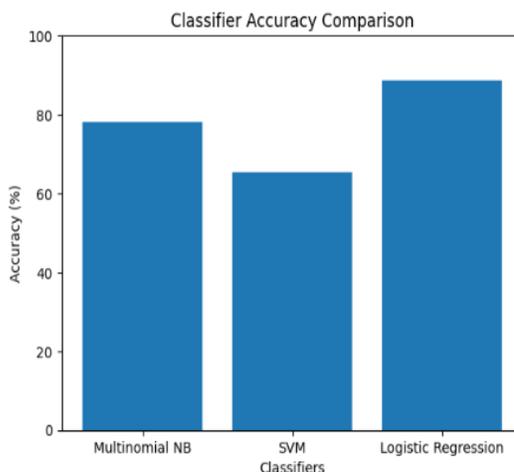


Fig. 4 graphical comparison of classifier accuracy

TABLE 1. Result

Classifiers	Accuracy In Percent(%)
Multinomial NB	78
Support Vector Machine(SVC)	65.43
Logistic Regression(LR)	88.76

5. Conclusion

Asthma monitoring systems driven by AI are revolutionizing respiratory healthcare by offering individualized therapy, real-time tracking, and predictive alerts. The quality of life for asthma sufferers can be improved disease management made possible by developments in wearable sensors, smart inhalers, and AI-driven analytics. To predict respiratory imbalance Asthma disease in the proposed study, we applied machine learning boosting techniques. It resembles respiratory disorder somewhat. Both physical and mental health is affected by this condition. The dataset has been taken into consideration for the input data for the ML algorithms during training and testing. We demonstrate the effectiveness of Logistic Regression classifiers on the provided dataset with **88.76** percent accuracy. In order to secure IoT-based health- monitor solutions and safeguard the wider ecosystem as well as sensitive patient and stakeholder data, an effective identity management system is the key. With transparency, portability, and simple management, these techniques could provide identity bearers complete ownership and control over their identities. Future research will examine verbal semantic cues, visual head attitude and eye-gaze cues, physiological cues including skin conductance and heartbeat, as well as advanced smartphone usage factors.

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