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A Comprehensive Framework for Epidemic Response in Smart cities through Machine Learning and NFA

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Abstract: Expertise in early detection against intimidating devastation using preventive procedure is an extremely challenging mission of this modern civilization. Sudden increases in the number of cases of disease threaten public health security. Guiding the public for the period of emergency situations plays a crucial role and this procedure saves countless lives. In this paper, we have developed a predictive model. When Epidemic predicted earlier on a proper and speedy response, the losses can be mitigated with the help of learning technology in AI. We proposed a comprehensive framework for the Epidemic management system which employs cumulated knowledge base construction through Machine Learning and Non-Deterministic Finite Automata technique. In this investigation, Real-time data acquisition, sharing accurate information and precise decision making are greatly augmented. This proposed model will enhance the government agencies and responders to act upon at all outbreaks.

Keywords: Epidemic Detectors, Fog Computing, Preparedness system, IoT Devices, Machine Learning Algorithms, NFA Techniques.

I. INTRODUCTION

An unpleasant sudden spread of the diseases within a short period of identical time affects a high count of people called Epidemic. The occurrence of sudden disease increases the high rate of illness and different varieties of symptoms. To minimize these impacts of diseases epidemic management system describes the important processes specifically, predicting, preventing, responding and controlling to improve public health security. This outbreak process reduces the severity as well as limits its spread.

The epidemic affects health, social security, and economic consequences. Disease outbreak helps to manage optimally in an emergency situation. Deployment of the newly developed preparedness system architecture along with readiness towards epidemic calamity helps the responders or stakeholders to get alert and limit the severity against the disaster. Minimizing the anticipation is a major task [1]. Detecting the severity, controlling the spread of the disease takes place with the help of this ideal system.

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Information exchange plays a vital role to improvise the speed, Fog Computing technologies where implemented. Fog Computing identifies the urgency through sensors and objects that are connected with each other without the need of a wider network. Data collection network connected wider because of the data exchange and data integration. Quick actions upon accurate real-time information are taken place by Fog Computing Technologies [2]. To help the needy people this emerging technology provides the facility to track the people, track the disease, track the health system and finally track the environment. Epidemic disaster can be classified as,

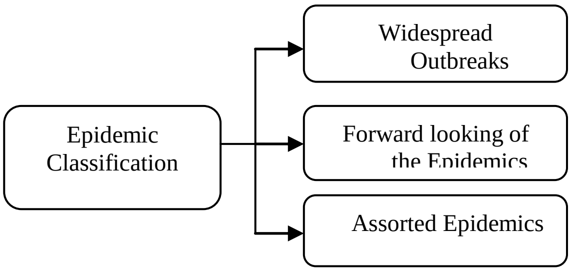

Fig. 1. Types of Epidemic Disaster

a) Widespread basis Outbreaks:

This infection spreads to a group of people from eating contaminated food. This disaster is identified from the time the food is taken and the number of people falls ill is calculated [3]

b) Forward-Looking of the Epidemics:

This infection spreads from person to person via directly or indirectly. The direct infection spreads through handshaking and interacting with each other. Indirect spreads via mosquitoes, contaminated water, and bacterial infected food intake. Malaria is the best example of this propagated disaster.

c) Assorted Epidemics:

This disaster mixes both common as well as propagated. Spread actually starts from the common outbreak and followed by a propagated disaster. Typhoid is the best example of this epidemic. Contaminated water intake reflects fever, and this fever spreads among the people. Out of this fever spread severity, this Epidemic preparedness system helping the people to come out from the disaster and make the people study the impact of the disaster management [4].

A. Authenticated Statistics Of The Epidemic Affected Regions [6]

These year-wise maps show the region-wise epidemic disaster-affected in the last five years. An incident of the disaster was shown and gives clear knowledge about the epidemic disaster [7].

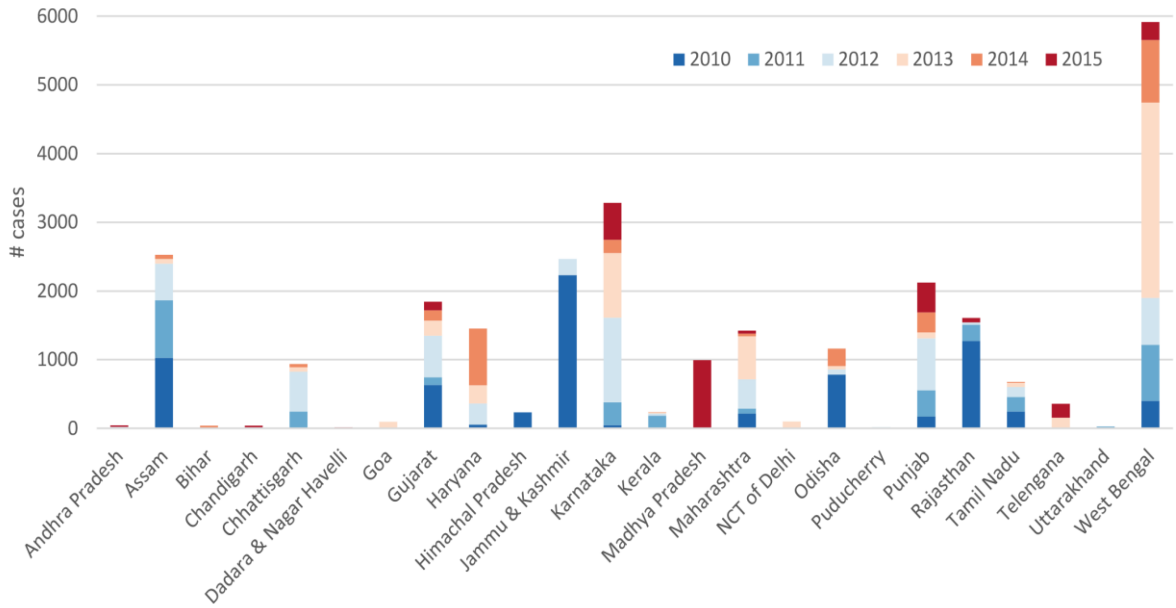

Fig. 2. No. of Cases affected by Epidemic in State Wise [7].

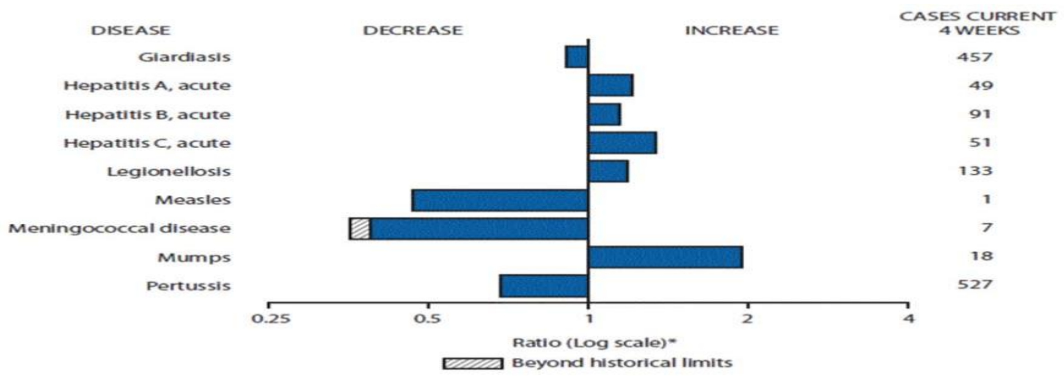

Fig.3 Disease proportion and Current Scenario [8].

B. Justification For The Need Of Epidemic Management System For Smart Cities

According to the developing country's statistics, an extra 50 percent of the inhabitants live in metropolitan areas. Forty percent of the people are going to shift from an urban area to the cities in 2030. Fast-growing cities spread diseases by taking unhygienic foods, contaminated water, polluted air-breathing, and congested housing and also other aspects. Smart cities need decongestion, safeguarding people against polluted environments [8]. Citizens should be informed about the crucial risk factors and precautions against the risks. Giving instructions about the preparedness system to the slum people is essential.

C. Steps Involved In Epidemic Exploration

To be in command of the multiply of the syndrome, an investigation is essential. This process involves professional intervention to identify the causes of the disease, the numeral of a community unnatural, and the mode of spread. This analysis involves the following steps to be initiated as soon as the disaster is identified by the experts [5].

1. Learning about open outbreaks.
2. Validate the identification of causes of the spread.
3. Reporting to the
   a. DHO (District Health Officers)
   b. Professionals such as Doctors, Nurses.
   c. Environmental experts
4. Carry out the explanatory or graphical Epidemiology report.
5. Build up a hypothesis to explain the occurrence of the Epidemics
6. Apply power or organize and protective measures
7. Correspond the findings to the higher levels in the health system such as
   a. Community Leaders
   b. Local Stake Holders.

II. PHASES OF THE EPIDEMIC PREPAREDNESS SYSTEM

Managing a crisis situation is the biggest risk. In this section, we would like to address the phases or the different stages of the preparedness system.

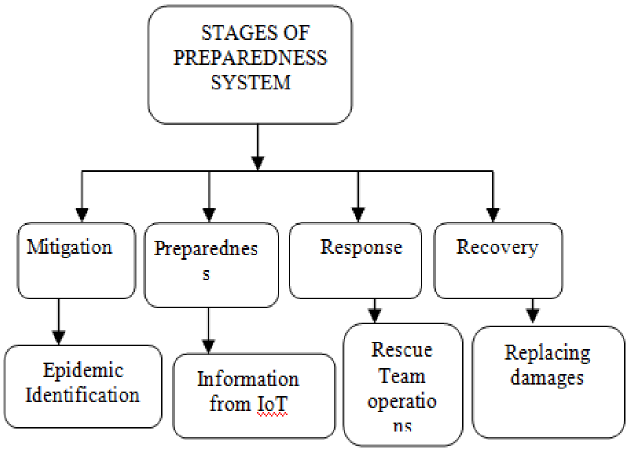

Fig. 4. Stages of Epidemic Management.

A. Preventive Measures

The foremost intention of this learning is to provide health security against calamity in urban areas. It determines and analyzes the disaster especially when healthcare is not available.

No. of infected people in an area = Symptoms identified from the people/ Total no. of people in an area × 100 [6].

Table – I Statistical Report On Infectious Diseases

DISEASE	SEVERITY	MAX. NO. PEOPLE AFFECTED	MODE OF COMMUNICATION
RABIES	MEDIUM	15 %	IoT SENSING
DENGUE	HIGH	30 %	SOCIAL NETWORK
PLAGUE	MINIMUM	5 %	SOCIAL NETWORK
MALARIA	HIGH	55 %	IoT SENSING

B. Framework For Epidemic Management System For Smart Cities

III. DEVELOPMENT OF THE PROPOSED MODEL

Digitization helps to integrate people, technology and faster processing to make better decisions at the right time. These integrated processes are taken place through real-time data acquisition, continuous diagnosis and analyze the sensors to develop a predictive model. Based on the sensor's data, prediction takes place and accurate decisions are made to inform the public to take the precautions against disasters [9].

A. Review On Machine Learning Techniques

Machine Learning is a scientific discipline and a subset of Artificial Intelligence. Machine Learns from experience without explicit programming to take accurate decisions at the right time. Predicting the future helps to save countless lives at the risk crisis. New models were created by training datasets. A newly arrived dataset is tested by the constructed model and the model predicts the accuracy then the model is trained excellently; otherwise, the model undergoes augmented training [10]. There are many Machine Learning Algorithms developed. In Supervised Learning, a model is trained by the datasets. Once the model gets trained, then it predicts accurately. In Unsupervised Learning Clusters were created from patterns and it learns from the observation. Reinforcement Learning is nothing but interaction with an environment. Rewarding the best results and trial and error method implemented. Based on the positive rewards machine trains and the new dataset are given based on the accurate prediction [25].

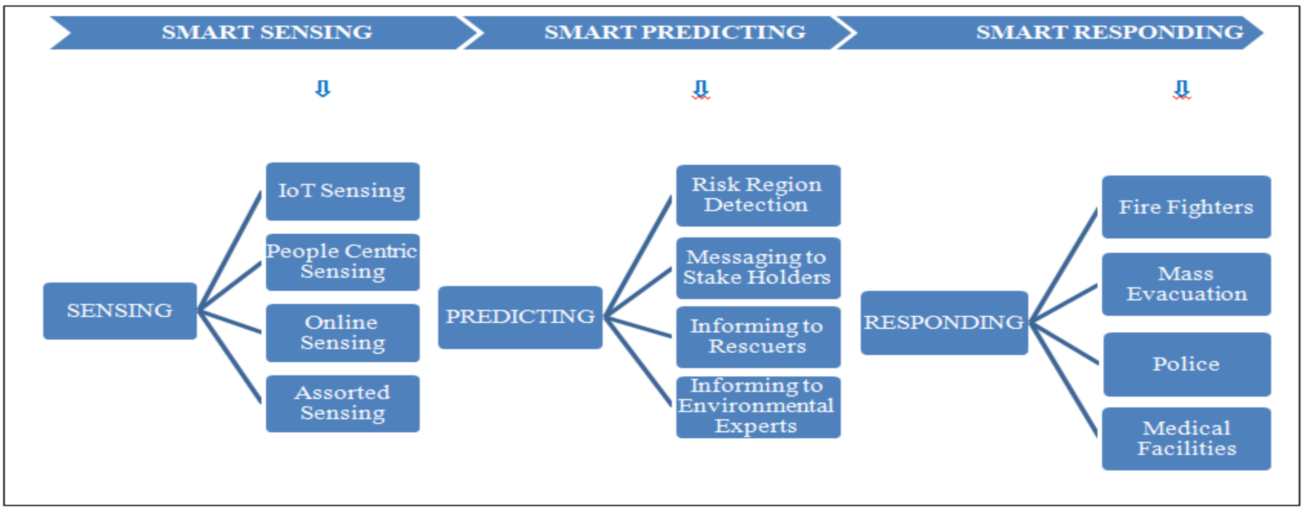

Fig. 5. Framework for Epidemic Management System for Smart Cities.

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This framework comprises sensing epidemic through IoT sensing, People-Centric sensing, online sensing and mixture of all these sensing called assorted Sensing. Once the streaming data is Received from the sensing phase, this data can be sent to perform the smart process called Predicting. The Last phase called smart Responding phase involves the Medical facilities, Mass Evacuation, informing the Fire and police stations. The main platform to analyze this investigation Machine Learning and Artificial Intelligence techniques and Knowledgebase representation were implemented to learn the epidemic, reason the Epidemic, predicting the disaster in advance, perceiving the Epidemic. This framework highlighted the main technologies, interactions, and components that are involved to predict the Epidemic well in advance. The smart system gives us the proposed method to develop the precautions as well as the recovery of the affected regions. Accurate prediction influences environmental experts to know about the disaster. Environmental experts can also be able to access the risk group through the predictive system.

Table II. Performance Analysis On PCD Learning Method [26] [28] [29].

Influencing Factors	Space Complexity	Simple Implementation	Co Linearity	Noise Rate	Parametric Model	Time Complexity	Accuracy	Mean Absolute Error
PCD Learning Method	O(m)	Yes	75% to 77%	No	Yes	O(n)	99%	0.97

Note ** To expand comprehension about PCD Learning Method, refer [29].

C. Detecting

This paper includes support reference on a research paper called "Dichotomic Prediction of an event using Non-Deterministic Finite Automata". This has been published in International Conference on Computing, Power and Communication Technologies (GUCON 2019) IEEE Conference Record No 47222. We have compared PCD Learning Method with other methods and we found that our method gives the finest results in Space Complexity, Efficiency, Time is taken depict and Mean Absolute Error factors and its impact is very high. Our proposed method is extremely beneficial when compared with other methods. Training sets were considered as Knowledge Base Representation. That is from K_1 to K_n. Epidemic Management System considers five parameters to predict the crisis.

Total Number of regions in a city = 'a'

Total Number of People in a region = 'b'

Symptoms Identified = 'c'

Number of people in risk group ='d'

TimeLine (No. of Days) = 'e'

PCD Learning Method constructed through the event's occurrences. Events can be added accordingly as well as TD that is, test data can also be added. NFA is a representation to check the prediction. These expressions are efficiently implemented to achieve predictions. A formal definition of NFA contains five variables they are, $\{Q, \Sigma, \delta, q_0, F\}$

Where

$Q = \{ K_1, K_2, K_3, K_4, K_5 \ldots Kn \}$ – Training Sets

$\Sigma = \{a, b, c, d, e\}$ – Set of parameters

δ = Transition function $Q \times \Sigma$

q_0 = is the starting state

q_m = Set of final state

Let us consolidate the parameters into single formulae,

K_m = States = $\{ K_1, K_2, K_3, K_4, K_5 \ldots K_n \}$

K_1 = a b c d e

K_2 = b a c e d

K_3 = a b d e c

K_4 = d e a c b

K_5 = e d b c a

..

K_n = b a c e d and so on...

Consolidated Formula $K_m = 2a^1\ b^1\ d^1\ e^1 + a^2, 2b^2d^2\ e^2 + a^3b^3\ d^3\ 2c^3 + 2c^4\ d^4\ 2e^4 + a^5\ b^5c^5d^5e^5 \ldots\ldots\ldots + a^nb^nc^nd^ne^n$ (1)

Where p^1, p^2, p^3, p^4, p^5 are denoted as positions of the parameters. Let us consider the first transition $2a^1$, b^1, d^1, e^1 and derive the processing.

State Transition Diagram for Consolidated Formula "K_m "

Transaction flow from the first state to the final state K_m = 2abde

δ (a, ε) = {a}

δ (a, a) = {b}

δ (b, d) = {d}

δ (d, e) = {e}

$K_m = 2a^1\ b^1\ d^1\ e^1 + a^2, 2b^2d^2\ e^2 + a^3b^3\ d^3\ 2c^3 + 2c^4\ d^4\ 2e^4 + a^5\ b^5c^5d^5e^5$

String K_m = a2bde

δ (a, ε) = {a}

δ (a, b) = {b}

δ (b, b) = {d}

δ (d, e) = {e}

Where e ε F.

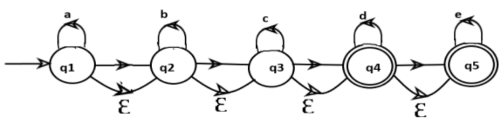

Fig. 6. State Transition Diagram.

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Table III. Transition Table For The Above Km Is

δ	a	b	c	d	e
q_1	$\{q_1\}$	$\{q_2\}$	Ø	Ø	Ø
q_2	Ø	$\{q_2\}$	$\{q_3\}$	Ø	Ø
q_3	Ø	Ø	$\{q_3\}$	$\{q_4\}$	Ø
q_4	Ø	Ø	Ø	$\{q_4\}$	$\{q_5\}$
q_5	Ø	Ø	Ø	Ø	$\{q_5\}$

The above mentioned Non-deterministic transitions start from the 'q_1' with the parameter 'a' and moves to q2 with the 'b' input parameter and other subsequent transitions are empty moves called 'Ø'. Likewise, the following transitions q_2, q_3, q_4, q_5 are taken place with the help of a, b, c, d, e input parameters.

D. Algorithm

1.Start
2.Initialize the Parameters for an event (x)
3.Comprehensiveness of the parametersEvent (x) = Where i=1,2,3……
9.Acquire the domain knowledge from various experts K(e1), K(e2)……………K(ex)
4.K(ex)
5.Where i = Number of Occurrences and j = Number of positions
6.Construct NFA for K(ex) with "m" states (q0, q1, q2…….qm) which is the model for testing new data.
7.Input the test data TD(i)
10.TD(i) =
11.Where y = 1 to z
12.Input TD(i) to q0 of NFA and perform state transition
13.If the end state qm is reached then "Event is predicted"
14.Else
15."Event is not predicted"
16.If e(x) is predicted k = k(ex) + TD(i)
17.Stop.

IV. STATISTICAL MODEL SUMMARY USING MULTIVARIATE ANALYSIS OF VARIANCE: A CASE STUDY

This experimentation has taken Vellore District's, (Tamil Nadu, India) population as a case study consideration. Total Number of regions, Number of people in regions, people in a risk group, year and timeline of the disease spread are the multivariate parameters. To increase the efficiency of the model MANOVA techniques were applied. If the factors are dependent on each other then this model helps to identify significance as well as integrate the standards of the system. To enhance the dependent variables which are correlated with each other then the capabilities of the method are improved [19].

Dependent variable 1 = Total Number of regions in a city = 'a Dependent variable 2 = Total Number of People in a region = 'b'

Dependent variable 3 = Symptoms Identified = 'c'

Dependent variable 4 = Number of people in risk group ='d'

Dependent variable 5 = Timeline or 2 (No. of days) = 'e' [30]

'Year' parameter is considered a decidedly dependent parameter among all the other parameters. This approach is beneficial during the epidemic prediction process.

Table IV. Statistical Model Summary

Model	R	R Square	Adjusted A Square	Std. The error of the Estimate	Durbin-Watson	F	Sig.
1	1.000[a]	1	0.997	0.068	2.054	540.59	.030[a]

The experimental results which we have received from Table IV state that regression between the parameters is a very secure relationship among themselves. The R-value shows the degree of determination and the value from the above table is .999 which means nearly 99 % of the people can be affected by the disease if the risk factor gets high. The dependent variable "year" has a direct and positive relationship with other parameters. The Durbin –Watson test shows the autocorrelation of 2.054 which is nearer to the optimum threshold level. F-value from the above table is 540.588, which states that the above model is highly significant.

Table V. Statistical Coefficient Summary

Model	Unstandardized Coefficients		Standardized Coefficients		
	B	Std. Error	Beta	t	Sig.
1 (Constant)	2024.651	.265		- 7.6543	.000
People in Risk Group	-.027	.001	- .775	- 25.245	.025
Symptoms detected	-.437	.018	-.750	- 24.433	.026

*Dependent Variable: Year

From the above Table-V shows the statistical summary of the coefficients of the regression model. The Beta values show that there exists a negative correlation involving the reliant variable and the independent variables. About 77.5% of the sample population is not falling under the risk group. Nearly 75% of the sample population tends to detected with the help of symptoms. These two independent variables, the p- values are statistically significant.

V. CONCLUSION

The main objective of this research is to enhance the efficacy of the Epidemic Response system by predicting the Epidemic well in advance from a set of parameters and undertake the remedies to mitigate the eventualities. We addressed the uncertainties and the difficulties faced by the epidemic disaster. Implemented Machine Learning Algorithm and PCD Learning Method to predict and respond to Epidemics efficiently and smartly. This system can also be utilized for other eventualities by changing the set of parameters. The proposed framework gives comprehensive knowledge about the workflow of the prediction process and also to direct the response team to make precise decisions in emergency situations. This study helps environmental experts' and health providers to predict the disaster in advance. Statistical representation called MANOVA method reveals this investigation has 95% of high significance which influences the system extremely powerful. In our subsequently research proposals we would like to confer implementation with Arduino, IoT Sensors and KAFKA Technologies for online streaming.

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