IDIC Theme Based Training Seminar: Application of Artificial Intelligence on Infectious Diseases and Infection Control

Forecast epidemics more effectively with Artificial Intelligence

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Definition of Infectious Disease



Infectious diseases are illnesses caused by various harmful organisms (pathogens) that can

be transmitted between humans, between animals, or between humans and animals.

Key Elements

Pathogen: Microorganisms that

cause diseases

- **Host:** Organism (human or animal)
 - infected by the pathogen
- **Omega Mode of transmission:** The way

pathogens transmitted from one

host to another

Modes of Transmission

Direct contact (e.g., skin contact, droplets)

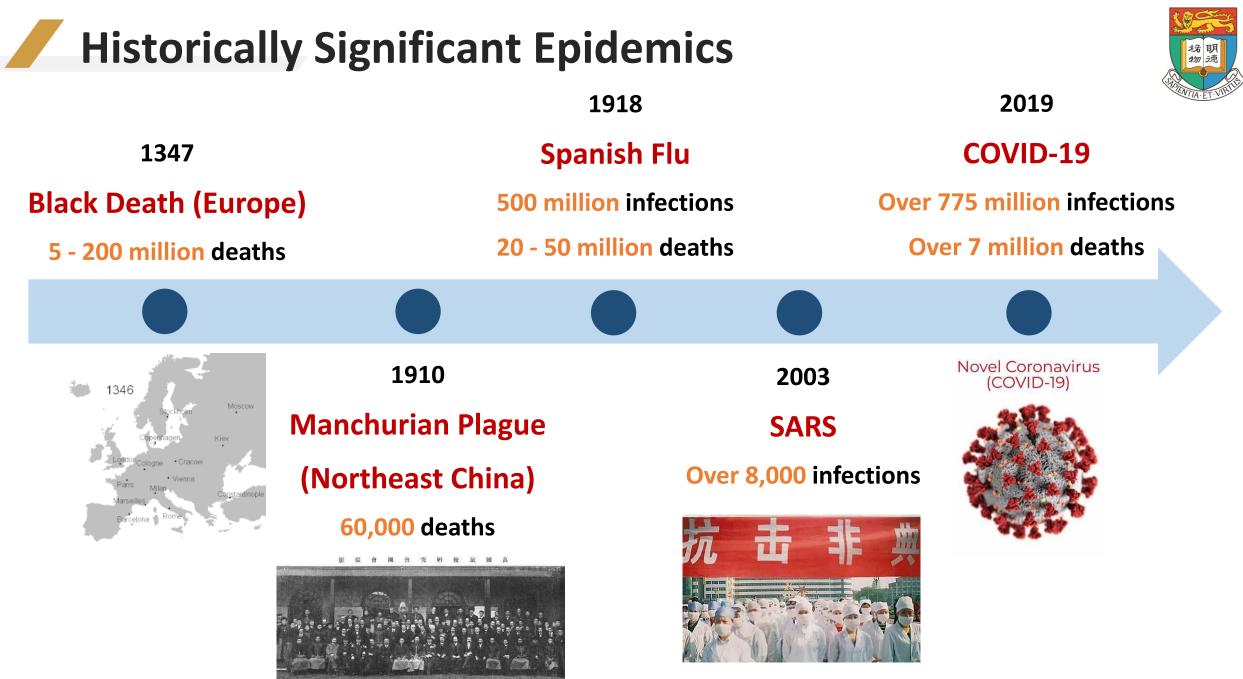
Indirect contact (e.g., through

contaminated water, food, or objects)

Airborne transmission

□Insect or animal bites

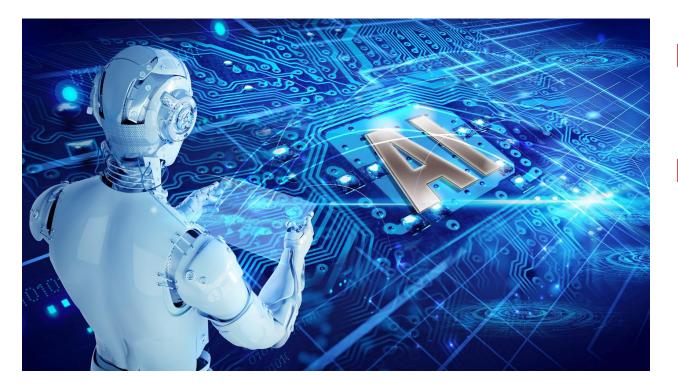




Definition of Artificial Intelligence



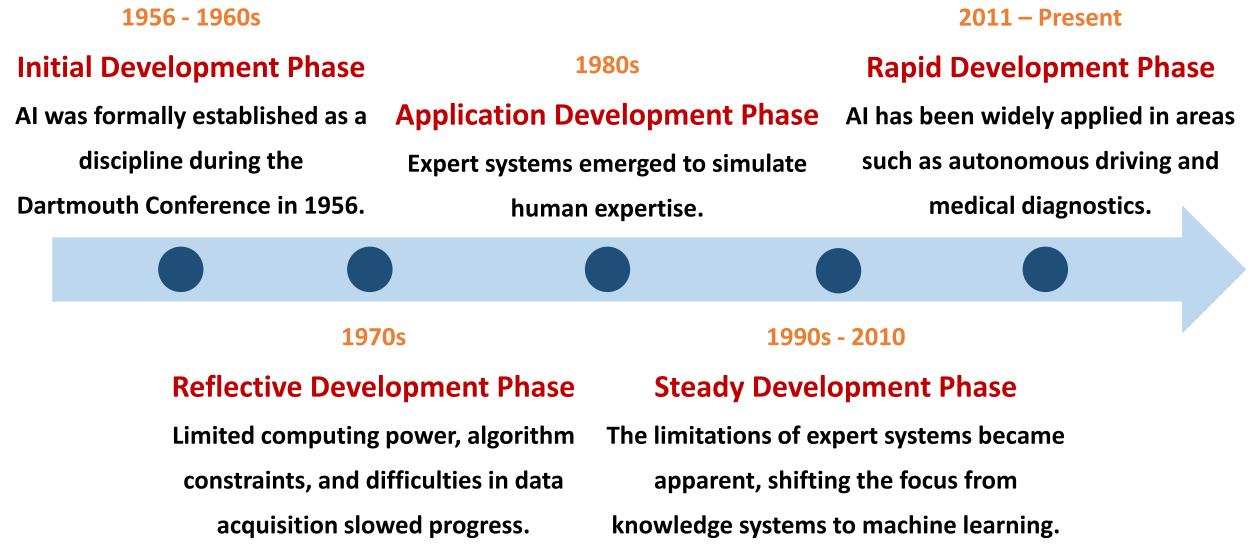
Artificial Intelligence (AI) is a field of science and technology that aims to simulate or replicate human intelligent behavior and capabilities.



 AI enables machines to exhibit characteristics of human intelligence
 AI encompasses multiple disciplines, including computer science, mathematics, neuroscience, and cognitive science.

Development of Artificial Intelligence





Applications of Artificial Intelligence

Healthcare

Rapid and accurate diagnosis of medical images using deep learning and machine learning
 Prediction of disease risk based on patients' genomic information
 Identification of potential disease risks by analyzing large healthcare datasets











Financial Industry

Analyzing big financial data to provide investors with accurate market analysis
 Utilizing deep learning and data mining techniques to better understand customer needs and behavior patterns, offering customized financial products and services
 Employing big data analytics and natural language processing to accurately identify anomalous transactions and fraudulent activities







Applications of Artificial Intelligence



Smart Transportation

Utilizing computer vision and sensor technologies to identify vehicles and pedestrians on the road, enabling autonomous driving and smart traffic management
 Optimizing traffic signal control and scheduling based on real-time traffic information
 Leveraging data-driven insights and improved operational visibility to enhance the efficiency, safety, and sustainability of ports and vessel











Smart Education

Using machine learning to automatically grade written work and provide feedback
 Analyzing students' assignments and exam responses to help teachers better

understand learning conditions and offer targeted guidance

Utilizing big data analysis and machine learning to assess student learning data and

behavior patterns, providing personalized learning plans and intelligent tutoring



MATHia



Traditional Methods for Infectious Disease Prediction

Relying on manually collected data reported by local public health agencies

Using traditional compartmental models like SEIR to simulate disease transmissions

Setting model parameters typically based on historical data or epidemiological studies

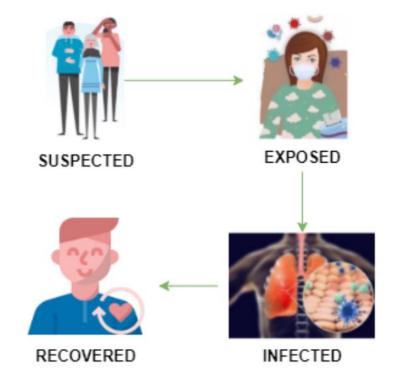
Disadvantages of Traditional Methods

Difficulty in timely reflecting the status of epidemic

Cumbersome and labor-intensive processes in data

collection and analysis

Slow data processing speeds resulting in delayed predictions and inefficiency





Artificial Intelligence in Infectious Disease Prediction

Collecting data from various sources, followed by preprocessing and cleaning

Using multiple algorithms to train on historical data and build transmission models

Combining deep learning models with time series data to forecast disease spread trend

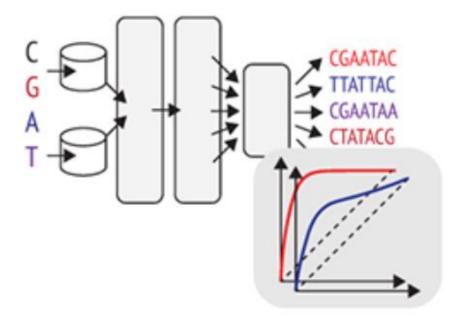
Advantages of Artificial Intelligence

CRapidly processing and analyzing data

Continuously optimizing models to accurately

identify infectious disease transmission patterns

Reducing manual intervention and enhancing prediction efficiency

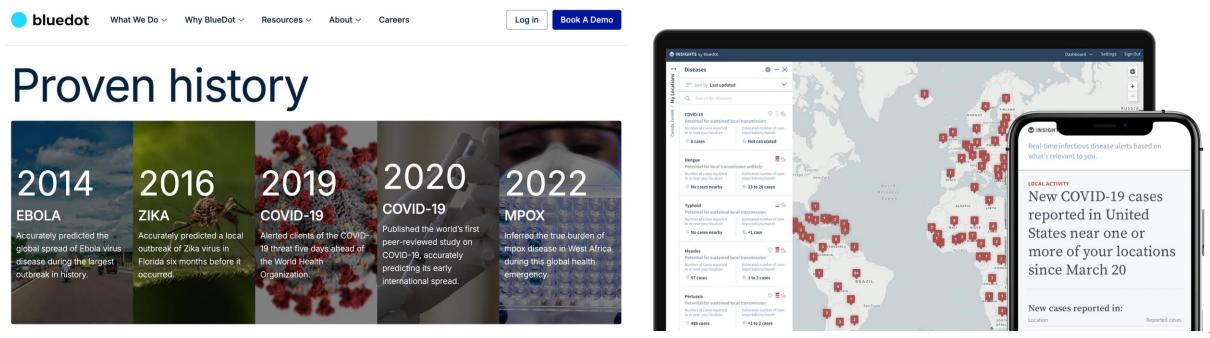




The monitoring platform developed by Canada's BlueDot can be used to assess regional

public health risks and the risk of disease outbreaks. Just weeks before the COVID-19

outbreak, BlueDot reported the potential for a pandemic, nine days ahead of the WHO's announcement.





□ The U.S.-based company MetaBiota uses natural language processing and other techniques to search unstructured data from social media, assessing the severity of infectious diseases. In early March 2020, MetaBiota's prediction of the COVID-19 outbreak deviated from the actual case count by only about 37,000.

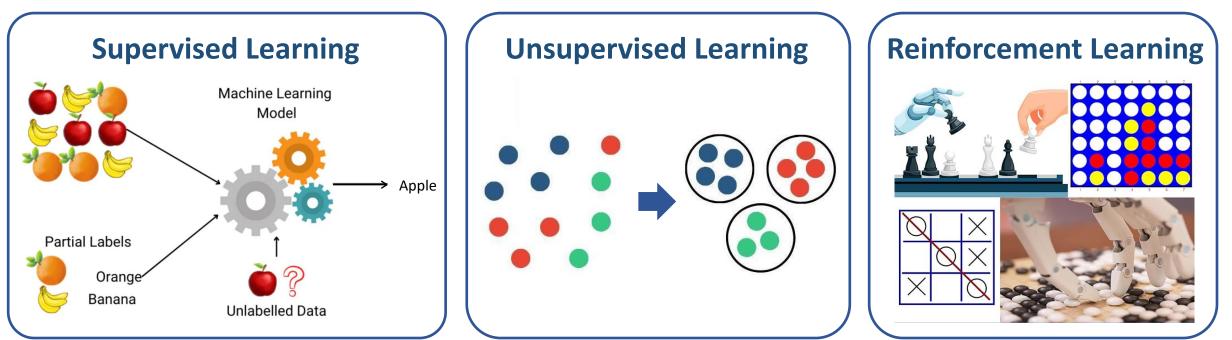
Outbreak Map	CHINA X	Q. Worldwide X				
Icefand Sweden Norway Russia	73 Index Score	ADD LOCATION ADD PATHOGEN SAV	YED SEARCHES			CLEAR ALL SEARCH
+ North North North North Mongolia app Pacific Ocean Turkey United States North image Ocean Turkey Turkey United States China image Ocean Turkisia Facilic North image Ocean Turkisia Facilic China image Ocean Mexico Ocean Image s Cuba Sensea Nigor Image s Colombia Democratic Penular Ophi	Rates and ranks sovereign states by their relative preparedness to detect and respond to an infectious disease epidemic (based on Index Factors below). Currently this index ranks a total of 188 sovereign states.	For ongoing outbreaks occurring V 43 PATHOGENS	Vorldwide from All Pathogens with 1 164 EVENTS	to 6,449,927 reported cases and 0 4,414,298 REPORTED CASES	to 4,933,189 reported deaths, th 16,427 REPORTED DEATHS	Here are: 100 YRS TIME FRAME SAVE THIS SEARCH EXPORT QUERY RESULT DATA
Peru Brazil Anton to Belivia South Vadagascar Indian ral: Preparedness Index Paraguay South Control South Ocean	Public Health Infrastructure (PHI) 68%	Location 🗘 Pathogen 🗘	Primary Transmission Type Reported Cases 🛟	Reported Deaths Case	Last Reported Days To Min Case Cases	First Reported 🗘 Source 🗘
Most Least Atlantic South Africa Usean Prepared Prepared Argentina Ocean	Aus Physical and Communications Infrastructure (PI) 70%	Mexico Viral conjunctivitis	Unclassified 1,405,217	0 01/01/2017	12/30/2017 0-6	Mexico Metabiota Best
Composition © OpenStreetMap Improve this map	Institutional Capacity (IC)	Yemen Vibrio cholerae	Waterborne, Fo 1,073,082	2,263 04/27/2017	03/04/2018 -	Yemen Metabiota Best
	Economic Factors (EF) V	Haiti Vibrio cholerae	Waterborne, Fo 815,219	9,694 10/17/2010	12/30/2017 0-6	Haiti Pan-American H
	Public Health Communication (PHC)	Japan Enterovirus	Unclassified 358,764	0 01/02/2017	12/31/2017 0-6	Japan Metabiota Best
		Sri Lanka Dengue virus	Vectorborne 185,688	320 01/01/2017	12/31/2017 0-30	Sri Lanka Metabiota Best





Machine Learning

Machine Learning (ML) is a subset of AI that focuses on enabling computers to learn from data and improve performance over time without explicit programming. In epidemiology, ML is used to analyze complex datasets, identify patterns, and make predictions.

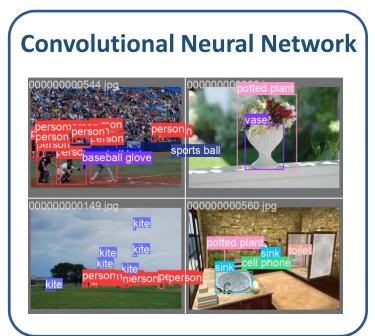


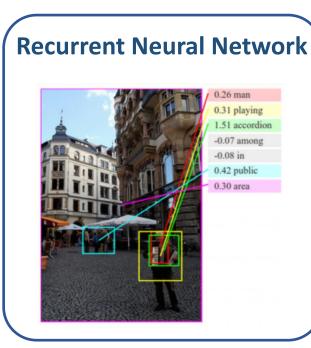


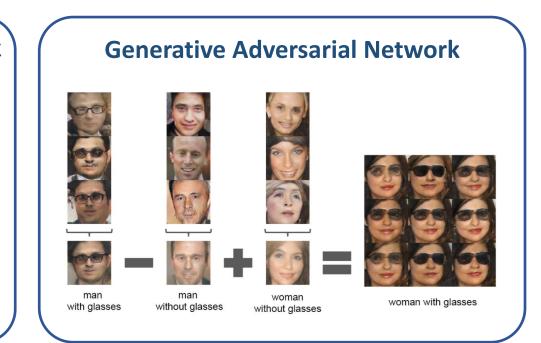


Deep Learning

Deep Learning (DL) is a key branch of machine learning that uses multi-layer neural networks (deep neural networks) to model complex patterns in data. It is particularly effective in image and speech recognition and can also be applied in epidemiology.







Key Artificial Intelligence Technologies

Natural Language Processing



Natural Language Processing (NLP) is a key area of AI focused on the interaction between computers and human language. It can analyze large amounts of text data, such as health records and social media posts, extracting valuable information to support subsequent simulations and analysis.



Automatic Summarization and Indexing
 Intelligent Recommendation Systems
 Speech Recognition and Generation
 Social Media Monitoring and Analysis
 Question-Answering Systems

Key Artificial Intelligence Applications

Applications of Al

- Risk Assessment
- **D** Early Warning
- **Disease Transmission Forecasting**
- Disease Personalized Prevention
- Transmission Chains Identification
- Pathogen Tracking
- Climate and Environmental Prediction
- **D** Regional Epidemic Monitoring
- Evaluating Control Measures







Manually collect large volumes of data, including field surveys, questionnaires, interviews, and case records — low efficiency; patient recall may introduce bias
 Utilize simple statistical methods to assess risk factors, followed by regression analysis to quantify risks — difficult to capture complex associations and nonlinear relationships

AI Methods

Employ various algorithms like NLP to extract symptoms and case information — high efficiency; real-time identification of potential outbreak signals
 Apply random forests on large datasets to identify disease transmission risk factors — enabling quantifiable precise risk assessment and insights into complex relationships

Application of AI: Risk Assessment

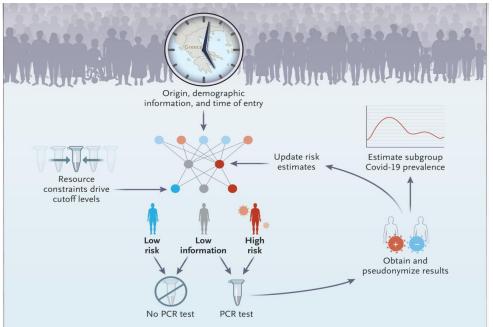
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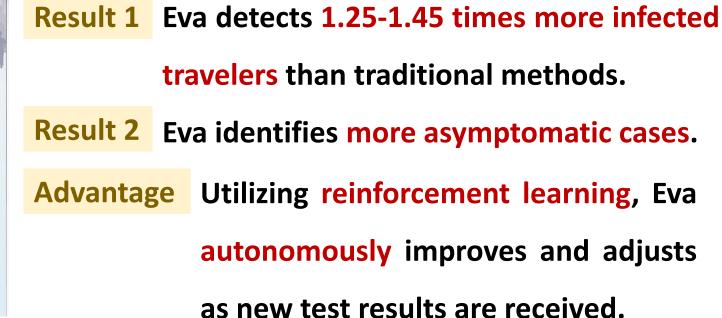
Case: Eva COVID-19 Border Surveillance System

The Greek government used the Eva system to screen incoming travelers for COVID-19.

Method real-time detection data 🕂 travelers' origin, age, gender, and arrival time 📫

assess risk and recommend who should undergo COVID-19 testing upon arrival









■ Rely on feedback from doctors and laboratories; diagnoses are based on patient symptoms and lab results (e.g., blood tests, PCR) — with delays in data collection and analysis leading to errors

AI Methods

Collect real-time data from multiple sources, processing it quickly to identify potential outbreak signals — broad data sources and enhanced processing capabilities
 Automate data handling to efficiently filter critical outbreak-related information — improving warning accuracy and enabling early intervention

Application of AI: Early Warning

Case: Google Flu Trends Predicts H1N1 Influenza in 2009



Google Flu Trends accurately forecasted H1N1 spread in the U.S. weeks before the outbreak

CDC required one to two weeks for similar predictions

Method 25 million search queries

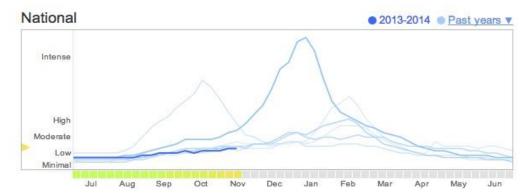
CDC flu data from 2003-2008

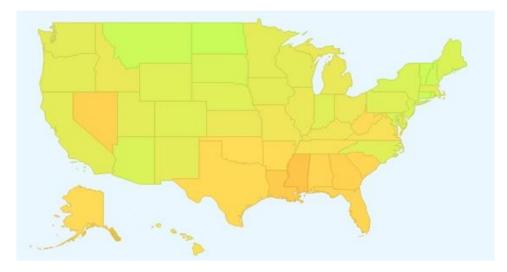
analyzed flurelated keywords predict case numbers and outbreak scope

using supervised learning models

Explore flu trends - United States

We've found that certain search terms are good indicators of flu activity. Google Flu Trends uses aggregated Google search data to estimate flu activity. Learn more »





Application of AI: Disease Transmission Forecasting



Traditional Methods

Rely on historical data and epidemiological theories for predictive models — manual

analysis of large datasets is time-consuming and does not reflect real-time conditions.

AI Methods

Integrate satellite images, climate data, and population movement information, using various algorithms to swiftly identify infection sources, transmission chains, and potential risks — enhancing accuracy in epidemic monitoring and early warning
 Efficiently collect and analyze data, model population movement, and assess migration's impact — enabling real-time monitoring of transmission speed and patterns

Application of AI: Disease Transmission Forecasting



Case: 2019 COVID-19 Prediction

Using big data from provincial health departments and AI techniques like natural language processing, 468 transmission chains were identified across 93 cities from January 21 to February 8, 2020

Result 1over 10% of transmission events hadnegative incubation period valuespotential subclinical infectionsResult 2serial interval: 8 days \rightarrow 3 days





CRely on patient history and lifestyle habits, with clinical experience and limited medical

records — limited data sources, subjective doctor judgment, lower prediction accuracy

AI Methods

DAnalyze vast health records, genomic data, and lifestyle habits to identify disease risks

- more precise risk assessment, offering personalized prevention

□Use recurrent neural networks like LSTMs to process time-series data, such as regular health checkups, predicting health trends and early signs of illness — enabling preventive interventions before symptoms appear

Application of AI: Disease Personalized Prevention



Case: Biobutton Wearable Device

□ Biobutton, developed by BioIntelliSense, is a wearable remote health device that

continuously monitors vital signs from the skin.

□ It collects 24/7 data without user input, using AI and big data models to automatically

detect abnormalities in real time.





 During outbreaks like COVID-19, Biobutton can identify early symptoms, triggering alerts to prompt isolation or medical attention.





CRely on epidemiological surveys and manual tracing through interviews with confirmed

cases, analyzing possible infection sources and pathways — time-consuming, depends

on patient recall and data completeness

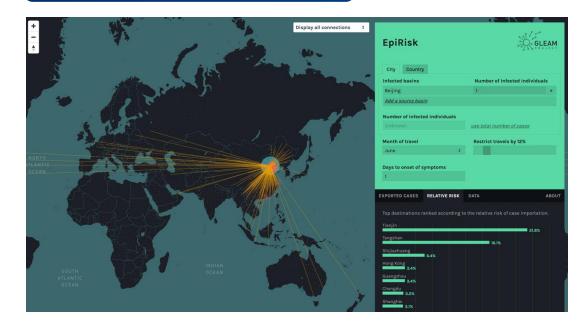
AI Methods

□Using neural networks to analyze multi-source travel and movement data, AI quickly identifies key transmission nodes and pathways — enabling rapid public health responses, such as enhanced monitoring and control in affected areas

Application of AI: Transmission Chains Identification



Case: GLEAM Platform



GLEAM is a global epidemic forecasting platform that integrates epidemiological models, big data, global population distribution, transportation networks, and human mobility to simulate disease spread and predict risks.



random forests decision trees neural networks...





Functionality

parameters like infection source, travel rates, and time



risk rankings resource allocation optimization...





DPCR and DNA sequencing compare genome data over time to identify mutations and

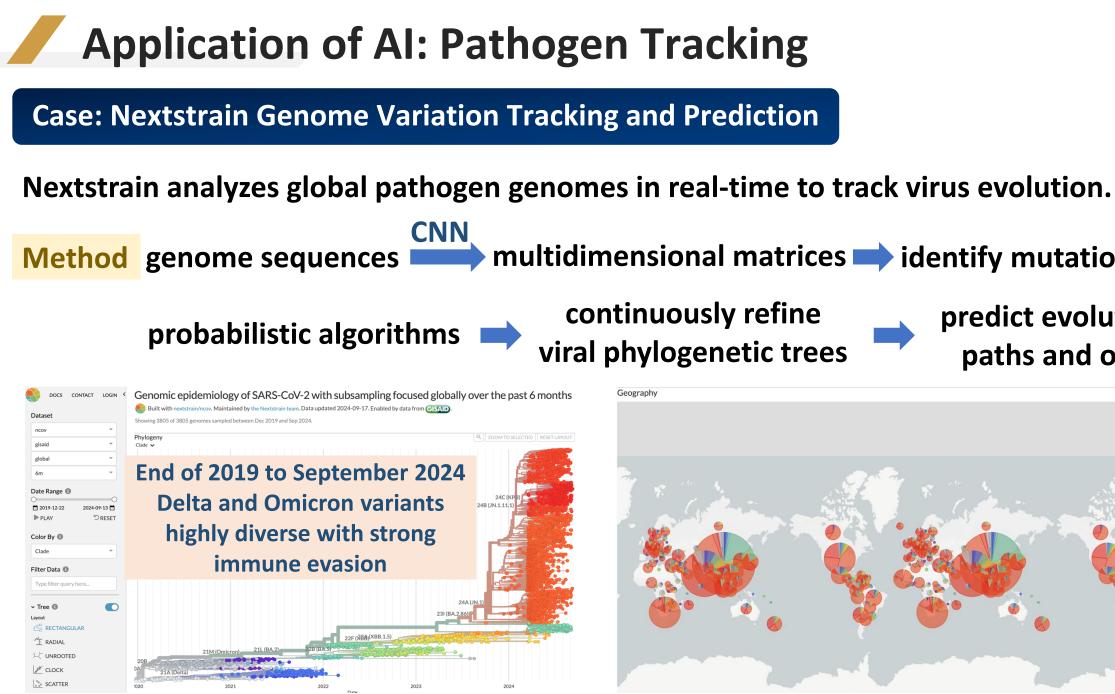
adaptations — relying on high-quality samples and lab conditions

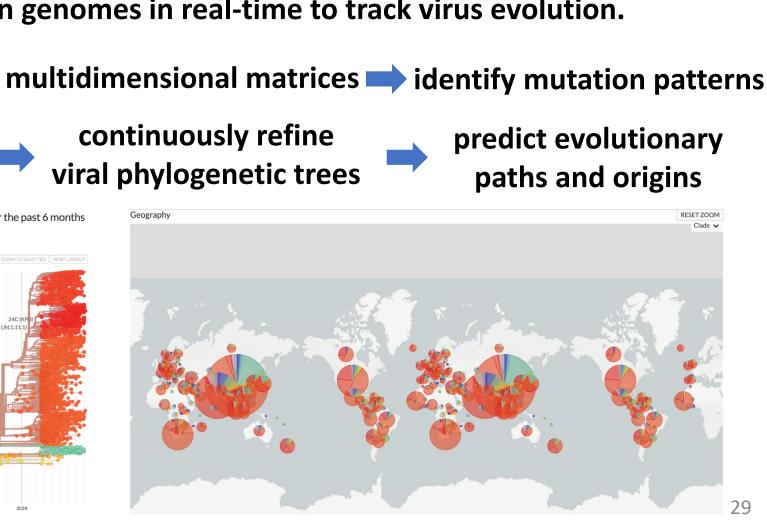
Rely on expertise and historical data to determine pathogen sources based on case and

contact tracing — subjective, limited by data quality and availability

AI Methods

Convolutional neural networks and sequence analysis quickly analyze pathogen genomes; clustering identifies strains with similar mutations and transmission paths; recurrent neural networks predict future mutations using historical data — enabling public health to swiftly adjust control measures





Application of AI: Climate and Environmental Prediction Traditional Methods Rely on static historical epidemic data and climate records for linear statistical modeling

- failing to reflect current environmental changes and disease transmission patterns

Rely on prior knowledge and assumptions, limiting the number of climate variables

processed — low prediction accuracy and lack of real-time updates

AI Methods

Utilize DL algorithms for complex modeling to analyze multidimensional climate factors affecting vector breeding — capturing nonlinear relationships and interactions
 Feature self-learning and real-time updates, dynamically predicting outbreak risks of mosquito-borne diseases — ensuring high accuracy and timeliness

Application of AI: Climate and Environmental Prediction

Case: Climate Engine Environmental Monitoring and Prediction Platform

Climate Engine analyzes global climate data and environmental changes, supporting

agriculture, water resource management, and public health.

Climate Engine utilizes satellite remote sensing, meteorological data, and climate models to generate high-risk alerts for mosquito-borne disease outbreaks.

Make Make Graph	MENU Map	Climate Engine.org	Make Make Map Graph	MENU Map	Climate Engine.org
GET MAP LAYER	Colors • Map • Layers • Masking • Download •	Link Reset Logout	GET MAP LAYER	Colors - Map - Layers - Masking - Download -	Link Reset Logout
Visualization Layer 📀	Mean Temperature (GEPS 4 Week Forecast)		Visualization Layer 🔊	Precipitation (GEPS 4 Week Forecast) 20-Ensemble Median forecast for 2024-09-19 to 2024-10-02, Total	20 40 60 80 Precipitation (mm)
Variable ? Type: Search Datasets Forecasts ~ Dataset: ? GEPS - 55km - 4week ~ Variable: ? Mean Temperature ~ Units: deg C ~ Computation	20-Ensemble Median forecast for 2024-09-19 to 2024-10-02, Mean	Mean Temperature (deg C)	Variable ⑦ Type: Search Datasets Forecasts Oataset: ⑦ GEPS - 55km - 4week Variable: ⑦ Precipitation (PPT) Units: millimeters Computation Resolution (Scale): ⑦	Get Value Get Value	STER STER Chicopo OFILIZON DECK DECK
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Rely on Geographic Information Systems to create epidemic hotspot maps for regional

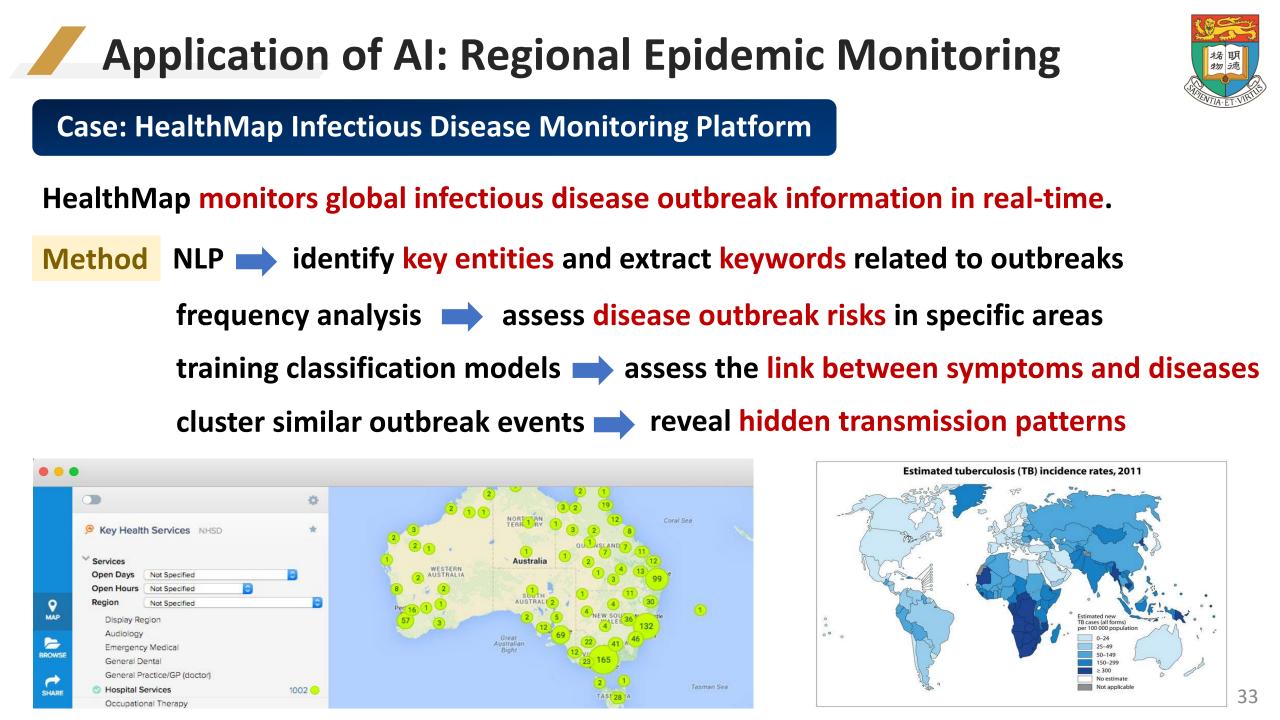
monitoring — challenges in ensuring accuracy and completeness of information

CRely on predefined spatial smoothing assumptions, such as similar epidemic conditions

in neighboring areas — limited spatial predictive capabilities

AI Methods

Utilize big data models to integrate diverse sources to extract key information like case counts and geographic locations — real-time monitoring of global infectious diseases
 Employ ML to identify epidemic hotspots and transmission patterns for early warning — assisting public health departments in quickly obtaining the latest information







Rely on surveys and polls to gather public opinion on vaccination and health policies —

limited coverage, lengthy data collection, and slow reflection of public sentiment

AI Methods

Use NLP to gather real-time feedback from social media on control measures — shortening data collection time and offering timely insights into public sentiment
 Combine epidemiological models and ML to simulate disease spread under different scenarios, such as varying vaccine doses or no vaccination — evaluate disease burden and cost-effectiveness to dynamically adjust control measures

Application of AI: Evaluating Control Measures



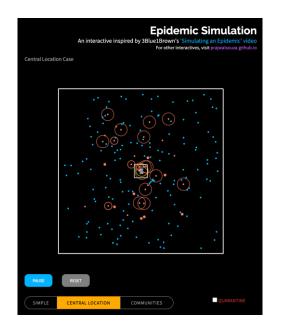
Case: Epidemic Simulation Platform

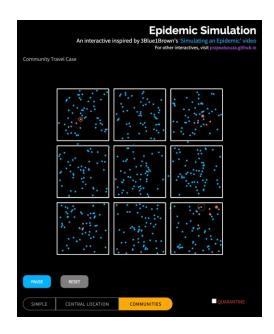
□Use the SIR model to simulate disease spread under various scenarios, comparing

infection numbers to quantify the effectiveness of control measures.

Combine RL to optimize interventions through a trial-and-error approach, while Bayesian inference is used to update model parameters in real-time.

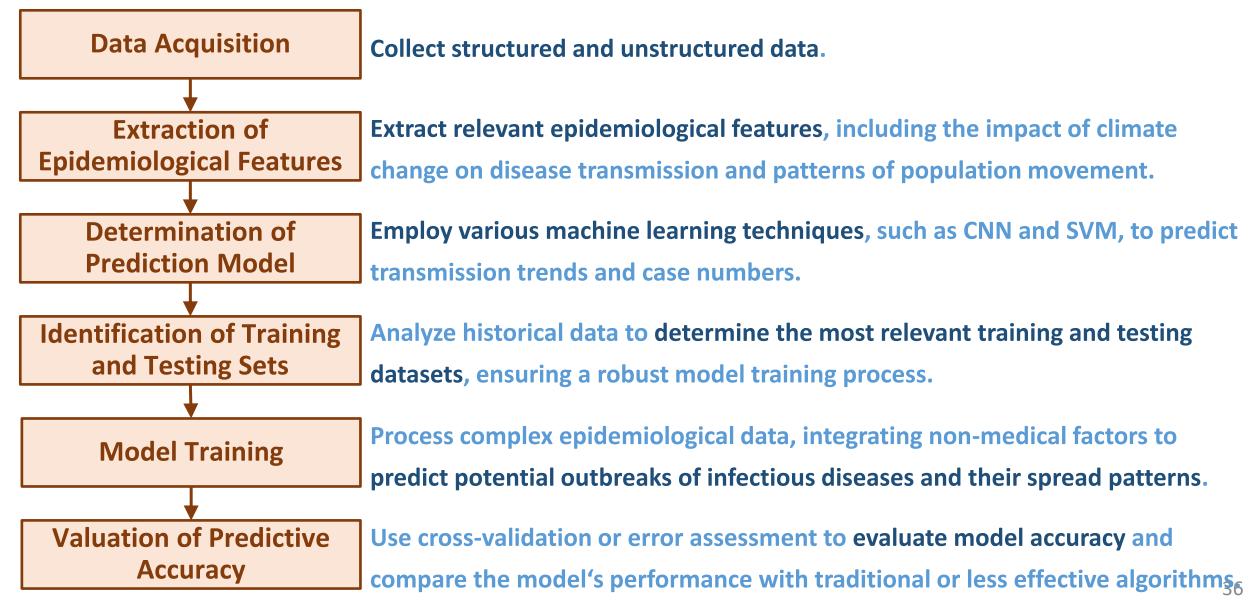
100 80 60	41.5% removed 17.5% susceptible	Simple Case	Epidemic Simulation An interactive inspired by 3Blue1Brown's 'Simulating an Epidemic' video For other interactives, viat projektiouza github.io
	41.0% infected		· · · · · · · · · · · · · · · · · · ·
PARAMETERS	Some parameters are specific to certain cases.		
Infection Radius 0.1	•		
Chance of Infection on a given day is 6%	•		
1% population/community infected initially (In community case, 1% of the community is infected initially, not the population.)			
Infection duration is 25 days	•		
Social Distancing Factor 0			• •
100% of the population obeys Social Distancing	•		•
Observe Social Distancing within 2 times the infection radius.	•	PAUSE	RESET
Please watch the 3b1b video to understand what is presented here. Parameters values here differ from the video and might give differen Please zoom in/out of simulation/graph if it doesn't fit into your scro	it results. een.	SIMPLE	CENTRAL LOCATION COMMUNITIES





Process of Predicting Infectious Diseases Using Al



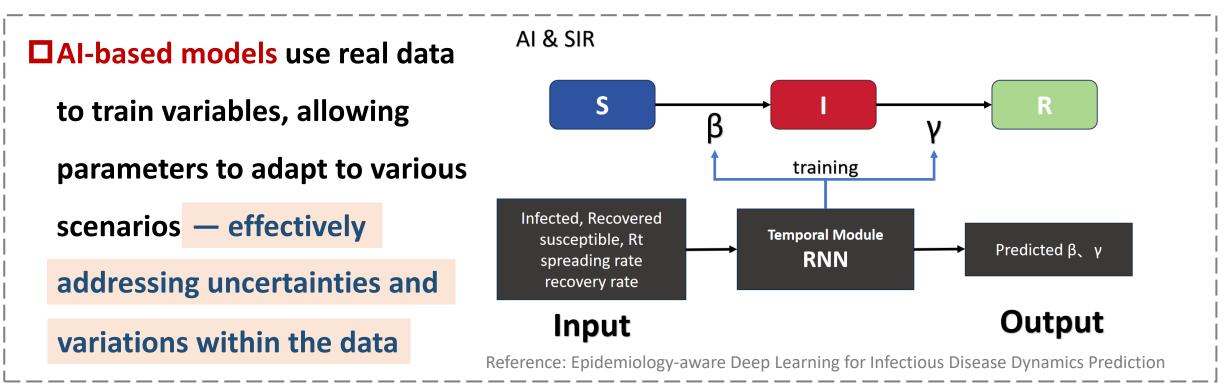




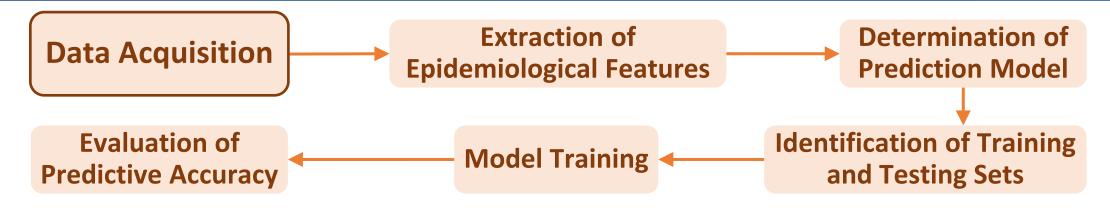
Training Epidemiological Parameters Based on AI Models

Traditional mechanistic models rely on preset or fixed epidemiological parameters –

struggle to adapt to the complex and dynamic real-world environment



Paper: Epidemiology-aware Deep Learning for Infectious Disease Dynamics Prediction



Utilizing a weekly dataset of

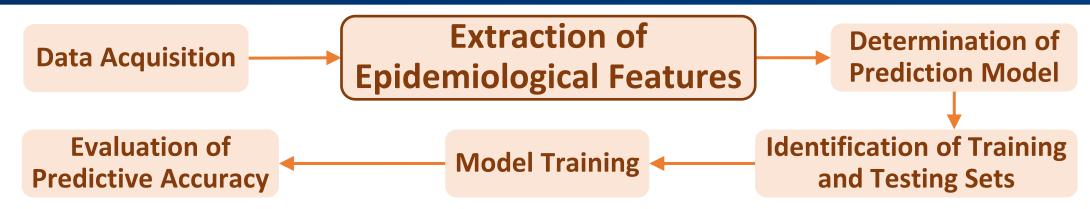
influenza-like illness activity from ten

U.S. regions, covering 364 weeks from

Week 1 of 2010 to Week 52 of 2016.



Paper: Epidemiology-aware Deep Learning for Infectious Disease Dynamics Prediction



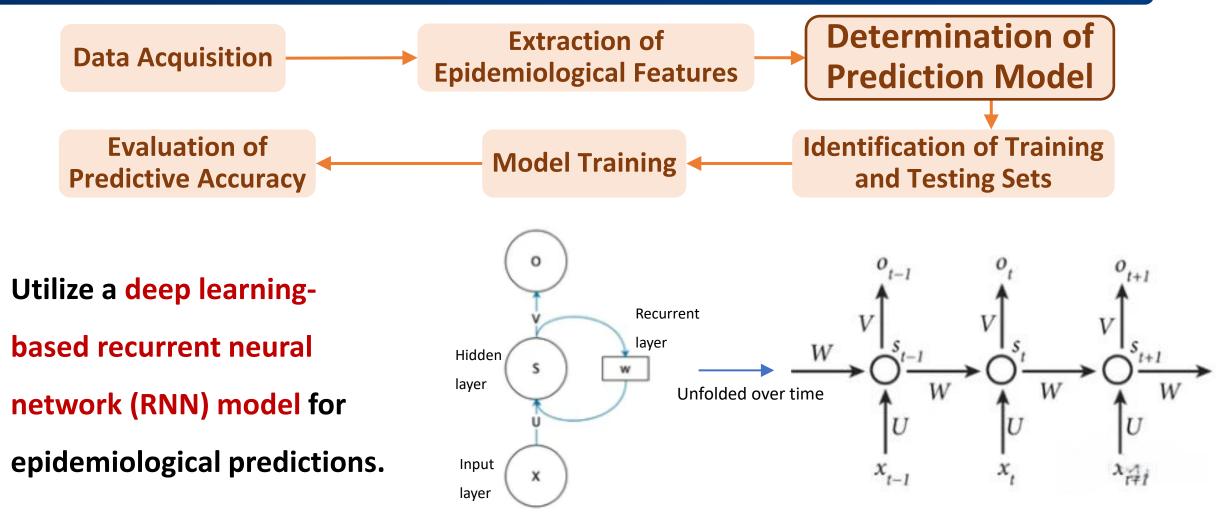
Input the historical data on epidemiological characteristics into the model:

including the number of susceptible, infected, and recovered individuals, as well as the

R

transmission rate, recovery rate, and basic reproduction number β V R0 = attack rate (AR) * number of contacts AR = 60% AR = 40% AR = 100%R0 = 3 R0 = 3 R0 = 5

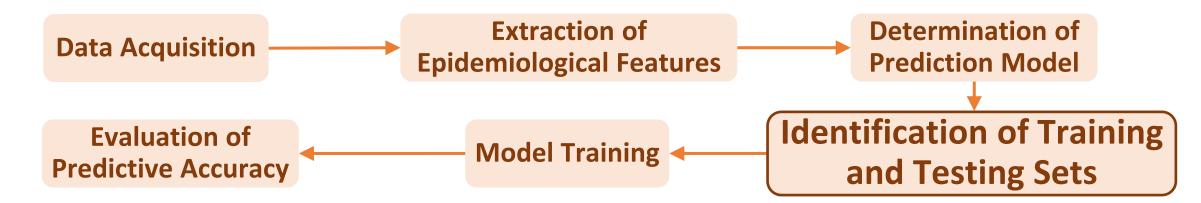
Paper: Epidemiology-aware Deep Learning for Infectious Disease Dynamics Prediction



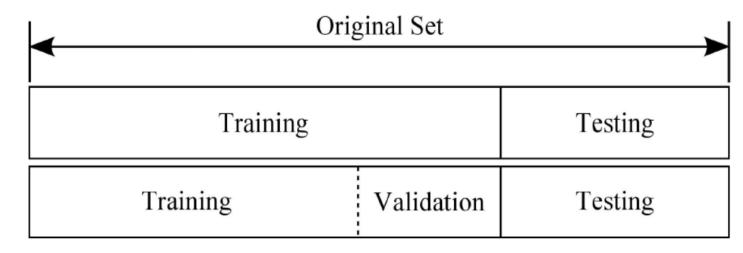
Principle of the RNN model



Paper: Epidemiology-aware Deep Learning for Infectious Disease Dynamics Prediction

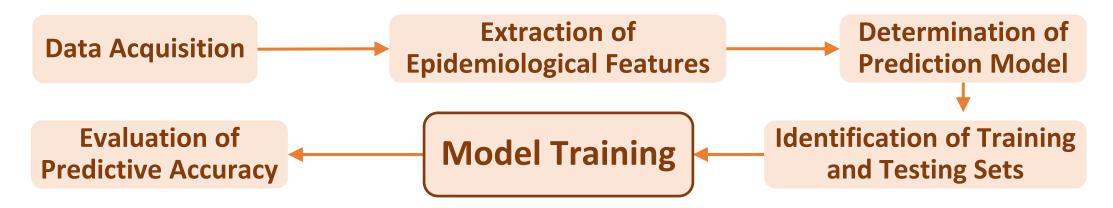


Divide historical data into training sets, testing sets, and validation sets in proportion to verify the accuracy of the prediction results.



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Paper: Epidemiology-aware Deep Learning for Infectious Disease Dynamics Prediction

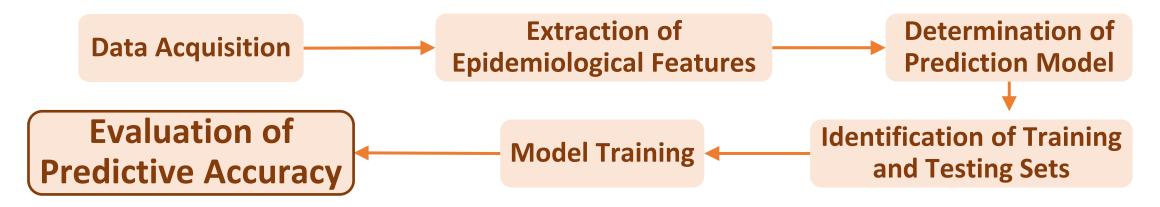


Input: Model receives historical data on infected, recovered, susceptible counts, transmission rate, recovery rate, and basic reproduction number.

- **Processing:** Model learns time-dependent features and updates internal state.
- **Output:** Network outputs predicted transmission and recovery rates.
- **Loss Calculation:** Predicted parameters simulate flu activity; difference with actual data forms the loss.
- Parameter Update: Parameters are updated based on loss gradient.



Paper: Epidemiology-aware Deep Learning for Infectious Disease Dynamics Prediction



Evaluate the model's predicted case numbers against actual cases using Mean Squared

Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

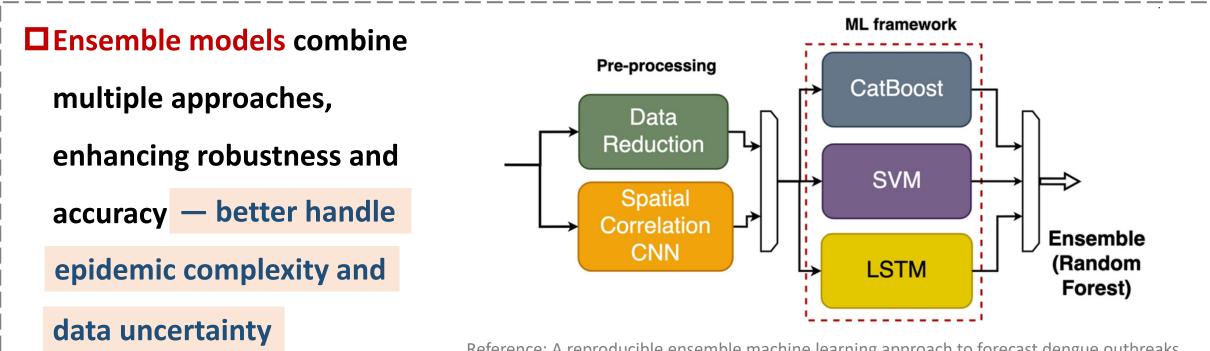
$$MSE= \frac{1}{m} \sum_{i=1}^{m} (y_i - y_i)^2 \quad RMSE= \sqrt{\frac{1}{m} \sum_{i=1}^{m} (y_i - y_i)^2} \quad MAE= \frac{1}{m} \sum_{i=1}^{m} |(y_i - y_i)|^2$$



Dengue Prediction Based on Ensemble Models

Traditional dengue forecasts rely on single models like time series or mechanistic

models — lacking accuracy due to data noise and parameter sensitivity



Reference: A reproducible ensemble machine learning approach to forecast dengue outbreaks

Paper: A reproducible ensemble machine learning approach to forecast dengue outbreaks

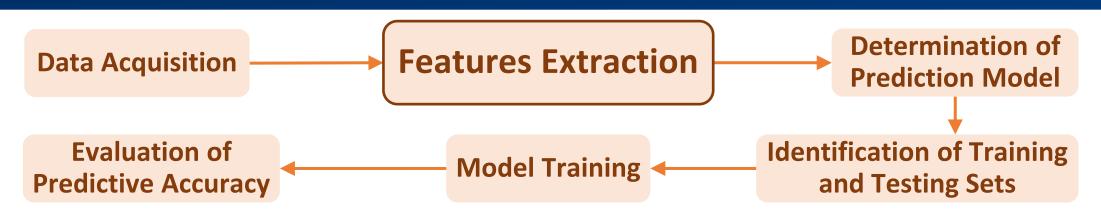


Medical Data: Monthly dengue incidence rate (DIR) in Brazil (2001–2019).

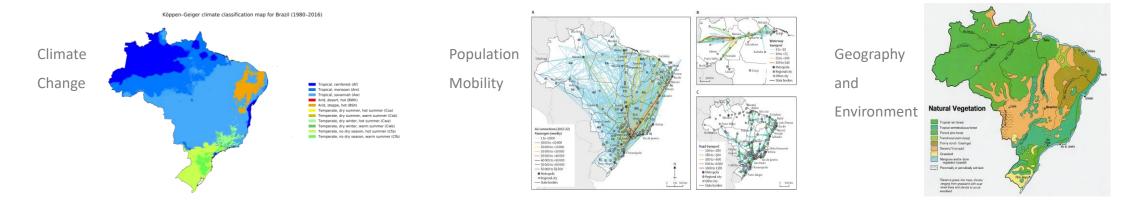
- Meteorological Data: Climate variables (temperature, rainfall, humidity, wind) from ERA5-Land and NDVI from MODIS.
- **Geographic Data:** Includes factors like geographic elevation.
- Socioeconomic Data: Includes population density, urbanization, road density, and social vulnerability index (SVI).



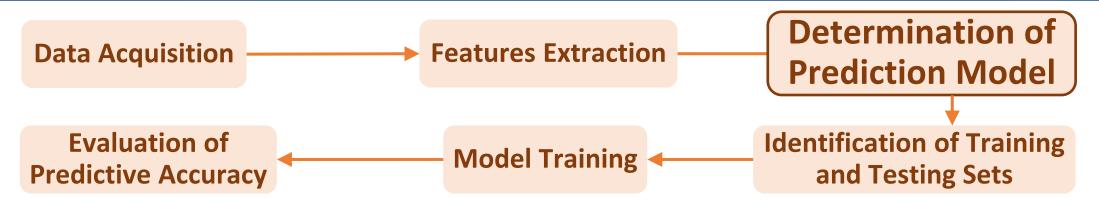
Paper: A reproducible ensemble machine learning approach to forecast dengue outbreaks



- Climate Change Impact: Temperature (max/min/average), rainfall, relative humidity, wind speed.
- **Population Mobility Patterns:** Social vulnerability index, population density, urbanization rate, road density.
- **Geographic and Environmental Features:** Geographic elevation, vegetation index.



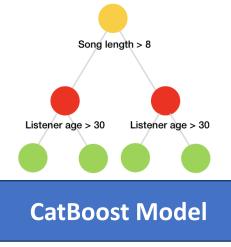
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- Meteorological Data: Temperature (max/min/average), rainfall, relative humidity, and wind speed.
- **Population Data:** Total population, 0-19 age ratio.
- Socioeconomic Data: Population density, urbanization level, and road density.
- Historical Dengue Data: Previous months' DIR.



A robust decision tree model suited for complex nonlinear relationships







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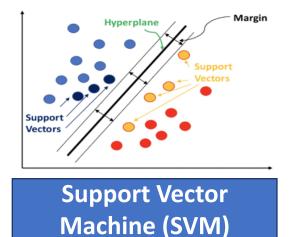
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A mathematically optimized algorithm that extracts useful patterns from data



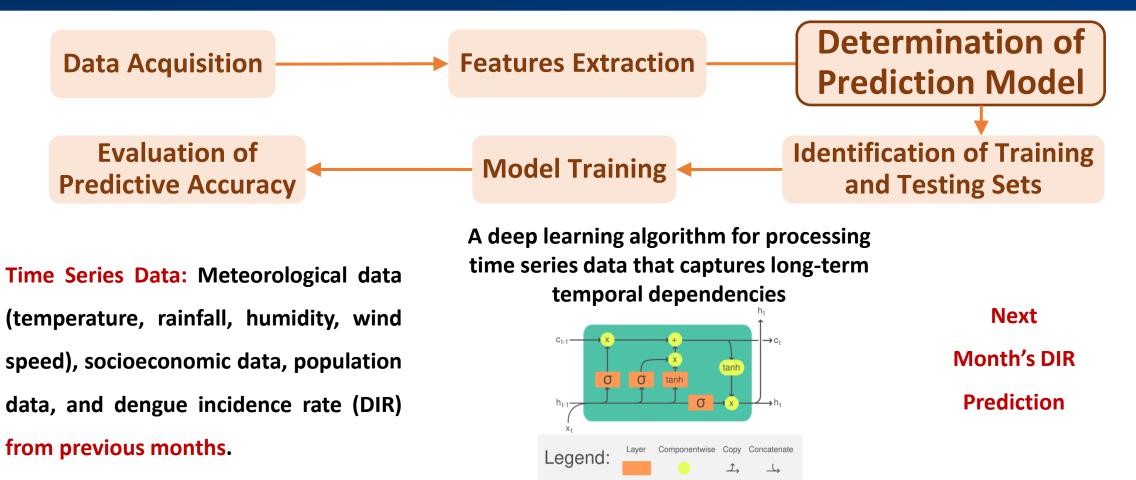




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Paper: A reproducible ensemble machine learning approach to forecast dengue outbreaks

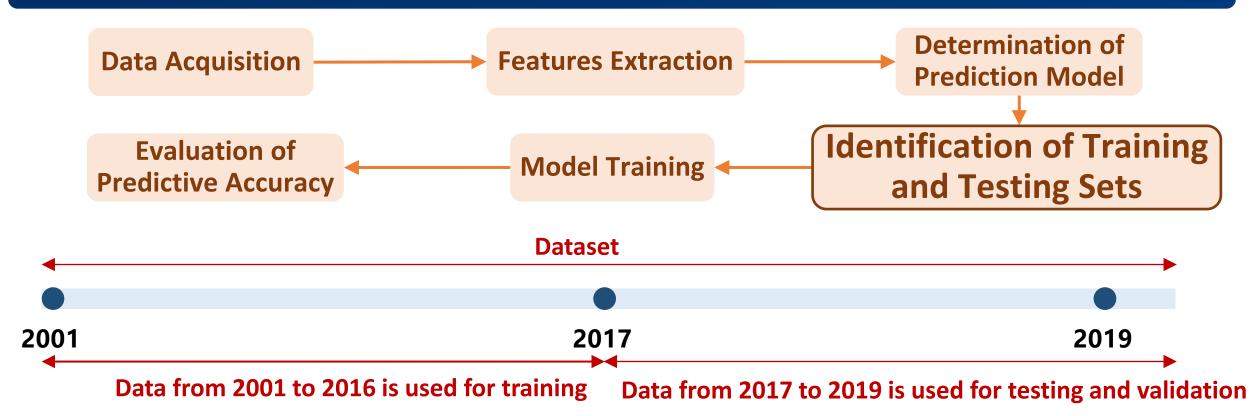




Long Short-Term Memory Network (LSTM)

Output

Paper: A reproducible ensemble machine learning approach to forecast dengue outbreaks



The model learns trends and correlations from historical data to accurately predict future dengue outbreaks.

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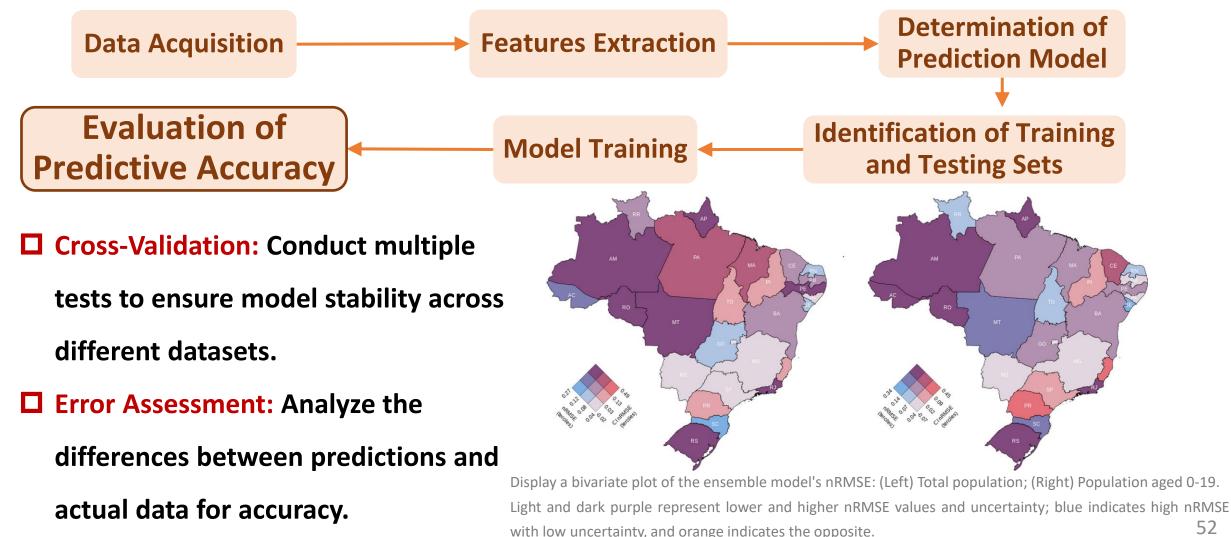
Input: Predictions from CatBoost, SVM, and LSTM serve as inputs for the random forest.

- Decision Tree Construction: Randomly select combinations of predictions to build multiple decision trees.
- Majority Voting: Each tree predicts based on its weight; the random forest combines these through majority voting or averaging for the final prediction.
- □ Final Output: Output the final predicted dengue incidence rate based on the votes or weighted averages from all decision trees.

Dengue Incidence Rate

Ensemble (Random Forest) 格 明 物 徳

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1. Enhanced Data Processing and Integration

AI will integrate multisource data, including health records, social media, traffic data, and climate data. This will enable the processing of complex, real-time datasets to improve prediction accuracy and identify potential outbreak points from multiple dimensions.



Health records

Social data

Traffic data

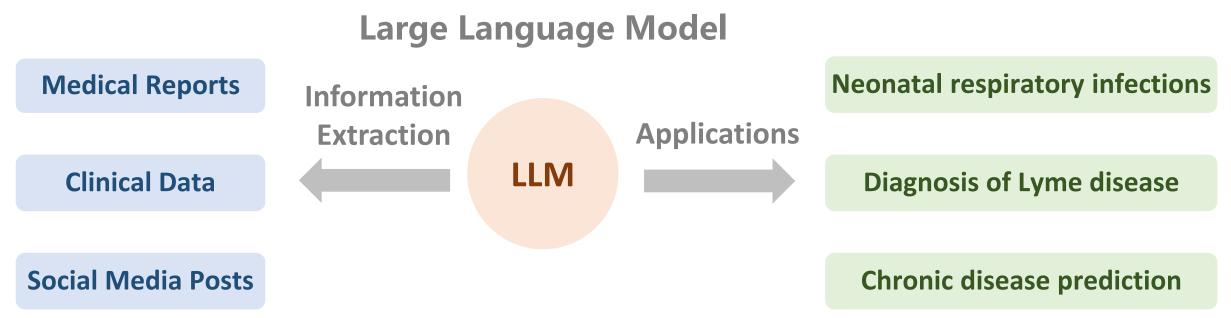
Climate data





2. Improved Processing of Unstructured Data

Large language models like GPT-4 can analyze extensive unstructured data, uncovering hidden trends and key information while saving time and resources.



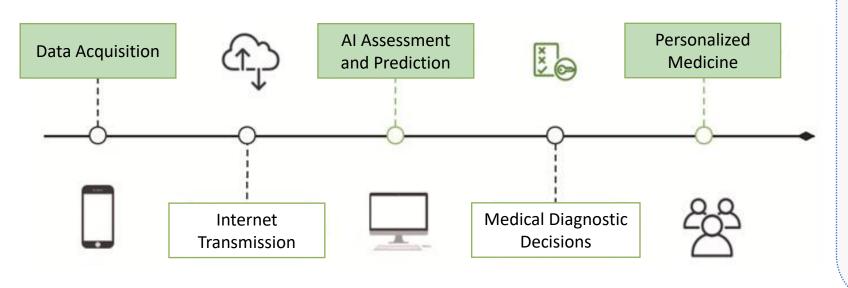




3. Personalized Infectious Disease Prediction

Future AI systems may offer tailored prediction models for various regions, age groups,

ethnicities, and socioeconomic backgrounds.



The Geisinger Health System in the U.S. has already used AI to personalize patient health data analysis and predict cardiovascular disease risk.

Development and Challenges of Al



Development

4. Multidisciplinary Integration **Economic Benefits** Treatment costs Direct The future of AI in infectious Non-medical costs disease prediction depends on ndirect Labor loss Drug Intervention Population Use integration with various. prevention Strategy Choice Without intervention With intervention Since 2023, RSV vaccines have ealth burden Plan 1 been approved. Health economic Plan 2 Plan 8 analysis can support pricing by assessing cost-effectiveness. AI + Health Economics

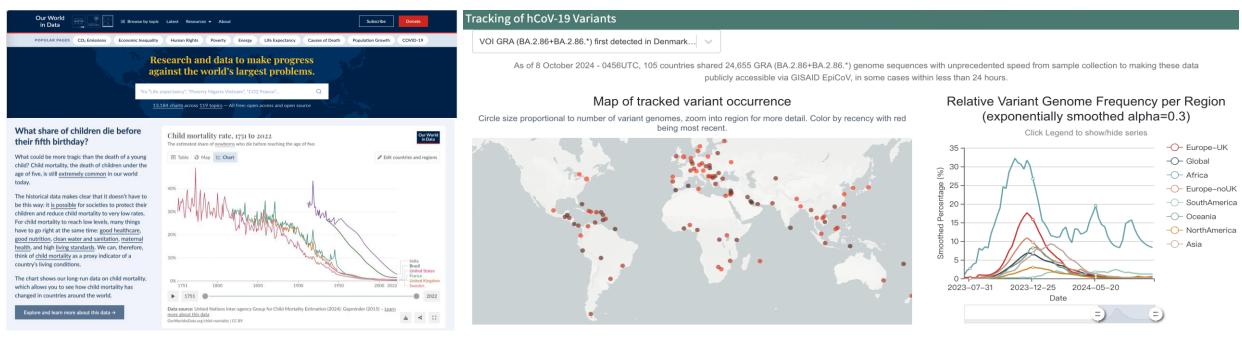




5. Global Data Sharing and Collaboration

Regions will establish unified open data platforms, enabling AI to learn from global data,

improving prediction accuracy and supporting disease control efforts.



Our World in Data



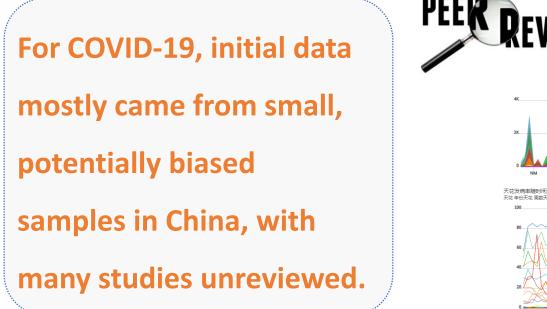


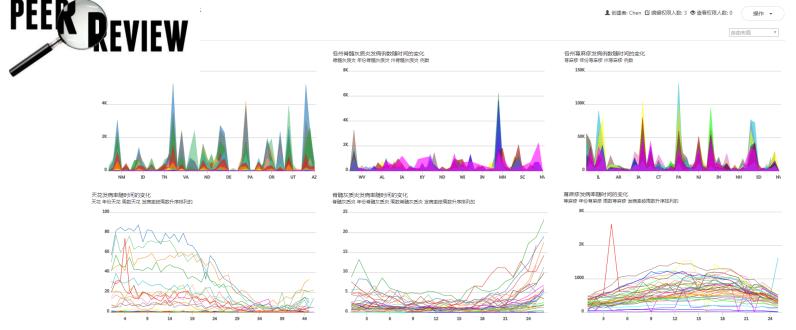
Challenges

1. Insufficient Historical Data

AI models need extensive, quality data, but early-stage outbreaks often lack sufficient

history and reliable databases, limiting tracking and prediction.









Challenges

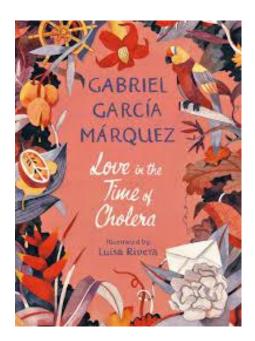
2. Data Quality Issues

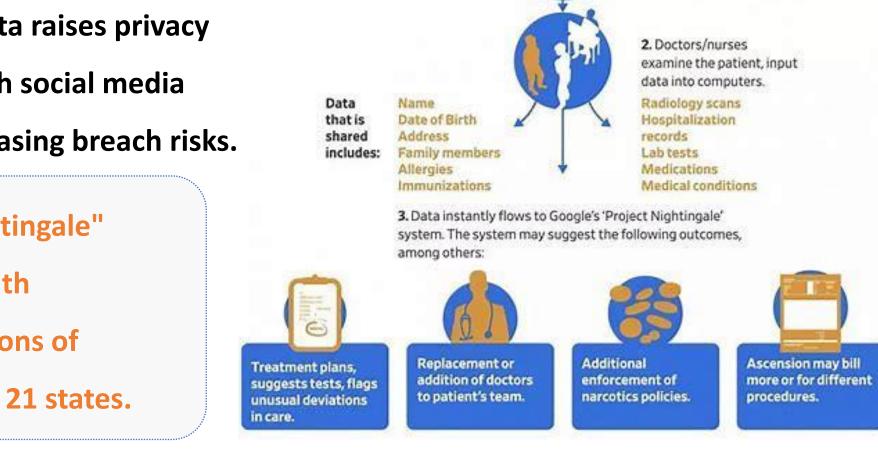
While big data sources like social media are abundant, they often contain significant noise

(e.g., misinformation), requiring filtering for accurate predictions.

In 2007, Google searches for "cholera" surged, not due to an outbreak, but because Oprah Winfrey selected the novel *Love in the Time of Cholera* for her book club.







How 'Project

Nightingale'

uses data

Development and Challenges of Al

Challenges

3. Ethical and Privacy Issues

Al's use of personal data raises privacy

issues, particularly with social media

and mobile data, increasing breach risks.

Google's "Project Nightingale" gathered detailed health information from millions of

unaware Americans in 21 states.

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Challenges

4. Algorithmic Bias Risks

AI models lacking diverse training data may worsen social inequalities.

During COVID-19, biased data caused U.S. algorithms to underestimate Black and Hispanic mortality differences by 60% and provide fewer care plans for non-White patients.



STATE ASSALLATION AND ALLOW





Thanks!

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